Comparing Edge-based and Node-based Methods on a Citation Prediction Task

Peter Vickers
Northeastern University
Boston, MA, 02115
USA
p.vickers@northeastern.edu

Kenneth W. Church
Northeastern University
Boston, MA, 02115
USA
k.church@northeastern.edu

Abstract

Citation Prediction, estimating whether paper a cites paper b, is particularly interesting in a forecasting setting where the model is trained on papers published before time t, and evaluated on papers published after $t + h$, where h is the forecast horizon. Performance improves with t (larger training sets) and degrades with h (longer forecast horizons). The trade-off between edge-based methods and node-based methods depends on t. Because edges grow faster than nodes, larger training sets favor edge-based methods. We introduce a new forecast-based Citation Prediction benchmark of 3 million papers to quantify these trends. Our benchmark shows that desirable policies for combining edge- and node-based methods depend on h and t. We release our benchmark, evaluation scripts, and embeddings.

1 Introduction

Citation Prediction is the task of predicting whether a given paper cites a target paper (Färber and Jatowt, 2020). Imagine the scenario where an author is writing a paper and is open to suggestions about what to cite. Consider a recommender system which will suggest papers in Semantic Scholar (S2)[1] (Ammar et al., 2018), a collection of 200 million academic papers from many fields.[2] Recommendations can be based on whatever is available in the input draft, including both text and references.

In order to make progress toward this ambitious goal, we introduce a new Citation Prediction task with an emphasis on the time dimension, and evaluate both a node-based model and an edge-based model on this task. The node-based model focuses on titles and abstracts, and the edge-based model focuses on citations.

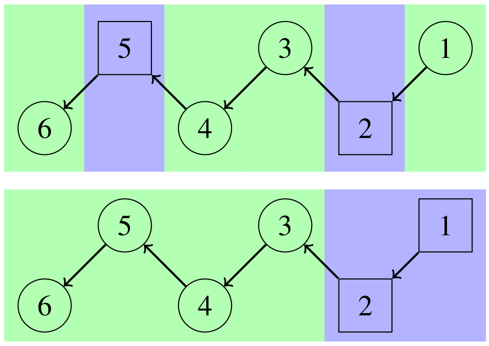

Figure 1: Random Splits (top) vs Proposed Causal Split (bottom) for Table 1. Train split in green, test in blue. The bottom plot with the train-test cut-off in 2010 gives a temporally consistent split.

Table 1: 1 cites 2, 2 cites 3,..., 5 cites 6

Paper	Year	Title
1	2018	[...] Photograment imaging
2	2016	Convenient probe of S(1D2)[...]
3	2005	Megapixel ion imaging [...]
4	2003	Direct current slide imaging [...]
5	1995	profiles of CI(2Pj) photoframents [...]
6	1988	Adiabatic dissociation of [...]

These models have not been previously compared with one another on graphs of different sizes, especially in a forecasting scenario. Standard benchmarks such as Open Graph Benchmark (OGB)[3] (Hu et al., 2020, 2021) and SciRepEval (Singh et al., 2022b) evaluate models such as Graph Neural Networks (GNNs)[4] (Scarselli et al., 2009; Zhou et al., 2018; Wu et al., 2019) and Specter (Cohan et al., 2020) on various academic document modelling tasks including citation prediction.

Unfortunately, most benchmarks are too small to see the region where edge-based methods overtake node-based methods. We expect citations (edges)

[1] https://www.semanticscholar.org/product/api

[2] Medicine (45M), Chemistry (13M), Computer Science (13M), Biology (13M), Materials Science (10M), Engineering (8M), Physics (7M), Psychology (7M), Mathematics (5M), Political Science (4M), Business (4M), Sociology (3M), Geography (3M), Economics (3M), Environmental Science (3M), Geology (3M), History (2M), Art (2M), Philosophy (1M).

[3] https://ogb.stanford.edu/docs/lsc/

[4] https://web.stanford.edu/class/cs224w/

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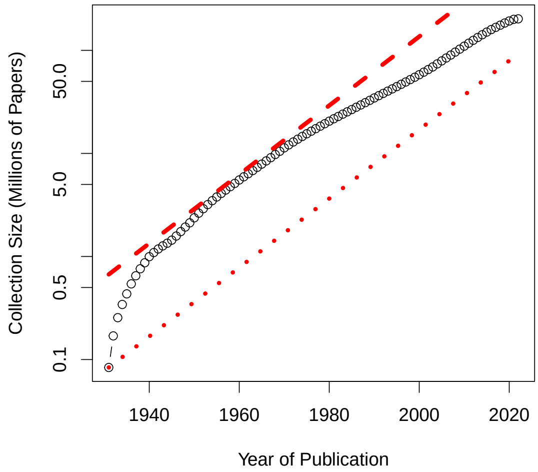

Figure 2: The literature doubles every nine years. Observations are denoted by circles and predictions by red lines.

to outperform text (nodes) when the graph is large enough because of network effects.

These scaling and forecasting issues are important for citation tasks because the literature is growing exponentially, doubling every 9 years[5] (Wade, 2022; Kinney et al., 2023). This growth rate is shown in Figure 2 for a collection of more than 200 million papers in Semantic Scholar (S2).

The scaling properties mentioned above are somewhat similar to Metcalfe's Law (Metcalfe, 2013). Metcalfe's Law applies when benefits scale with edges (n^2) and costs scale with vertices (n). In a telephone network, costs scale with subscribers (n), and benefits scale with connections between subscribers (n^2). These network effects are often cited[6] for the success of businesses such as telephones (AT&T), web search (Google) and social media (Facebook).

Our contributions are as follows:

1. A new benchmark for citation prediction emphasizing scale and forecasting.
2. Empirical demonstration that larger graphs favor edge-based methods.
3. Empirical evidence that performance improves with t (larger training sets) and degrades with h (forecasting horizon).
4. We release the TimeCite benchmark, evaluation code and embeddings.[7]

Following the demonstration of the effectiveness edge-based methods in this paper, we implemented such a recommendation system over Semantic Scholar. It is available at https://recommendpapers.xyz.

2 Related Work

There is a huge body of work on recommender systems (Resnick and Varian, 1997). The literature on citations is not as large, though still considerable:

- Early work: (Strohman et al., 2007; Bethard and Jurafsky, 2010; He et al., 2011; Caragea et al., 2013; Sugiyama and Kan, 2013)
- Benchmarks: OGB, SciRepEval and others (Roy, 2017)
- Evaluations on benchmarks: (Cohan et al., 2020; Singh et al., 2022a; Hu et al., 2021)
- Training models on benchmarks: (Yasunaga et al., 2022; Ostendorff et al., 2022)
- Survey papers: (Färber and Jatowt, 2020; Ali et al., 2020; Ma et al., 2020; Pillai and Deepthi, 2022; Liang and Lee, 2023)

There are a number of use cases that are related to citation prediction:

1. For authors: what should I cite?
2. For readers: what should I read? (Beel et al., 2015; Steinert, 2017)
3. For conference organizers: who should review what? (Dumais and Nielsen, 1992; Yarowsky and Florian, 1999; Mimno and McCallum, 2007; Zhang et al., 2023)
4. Finding experts (Yimam-Seid and Kobsa, 2003; Maybury, 2006; Tu et al., 2010): "Who knows" (Streeter and Lochbaum, 1988)

3 Methodology

3.1 Forecasting Citation Prediction

The Citation Prediction Task is simple: predicting whether paper v_k and v_l cite one another i.e. $(v_k, v_l) \in E$. We define the distance $d(v_k, v_l)$ as the length of the shortest path between vertices v_k and v_l in the citation graph. To make the task harder, we sample relatively challenging negatives,

[5] https://blogs.nature.com/news/2014/05/global-scientific-output-doubles-every-nine-years.html

[6] https://en.wikipedia.org/wiki/Metcalfe%27s_law

[7] https://github.com/petervickers/TimeCite

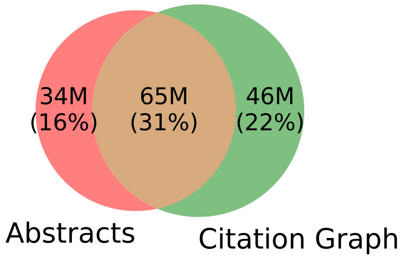

Figure 3: There are many missing values. Many papers have abstracts (99M) and many have links in the citation graph (111M), but only 65M (31%) have both.

where v_k and v_l are 2-4 hops from one another, i.e., $2 \leq d(v_k, v_l) \leq 4$.

Given the full Semantic Scholar citation graph G, we begin by taking random walks of up to 11 hops. These walks are then filtered with BFS to retain only those walks where $1 \leq d(v_k, v_l) \leq 4$. Verified walks are added to our evaluation dataset, structured as: $< v_k, v_l, d(v_k, v_l), \text{bin} >$, where v_k and v_l are two papers in a verified walk, and bin is $max(bin(v_k), bin(v_l))$, the bin of the more recent of the two papers. Binning is discussed in more detail in the next section.

3.2 Graph Partitioning

We construct a citation graph, G, based on data from S2. S2 maintains a dataset of around 200 million academic documents dating from 1684 CE up to the current time. Each entry has a primary document id. Document ids are often associated with a title, abstract and citations, though these values can be missing (and incorrect). Figure 3 shows that many papers have abstracts, A, and many papers have links in the citation graph, L, but relatively few have both. By construction, random walks are based on L and therefore, the proposed benchmark is a subset of L (papers with links).

To build a causal forecasting task we require a view of the graph which respects the time-dynamics of academic literature (Kuhn, 1962; Hall et al., 2008). To do this, we split the citation graph evolution into 100 chronological sub-graphs.

First, we construct a citation graph $G = (V, E)$, where:

- V is the set of vertices, $\{v_1, v_2, ...\}$, where v_i is a document id
- E is the set of edges. An edge is a pair of document ids, (v_i, v_j), where document v_i cites document v_j.

Each vertex, $v_i \in V$, has a publication date.[8] We use these dates to partition the 200 million total documents in V into the 100 equal-sized bins: $V_0, V_1, V_2, ...V_{99}$. Each bin contains approximately two million documents. Let $bin(v_k)$ indicate the bin for paper v_k. That is, if $v_k \in V_b$, then $bin(v_k)$ is b. $bin(v_k)$ is a number between 0 and 99. The bin of an edge, $bin((v_i, v_j))$, is $max(bin(v_i), bin(v_j))$, which is usually $bin(v_i)$ since edges are usually causal. That is, papers typically cite papers in the past, and rarely cite papers in the future.

Due to the exponential pace of paper publications in Figure 2, the first bin, V_0, encompasses papers from 1684 to 1936 CE, while the final bin, V_{99}, encapsulates papers from 2022 to 2023. More details are presented in Appendix A.

For each bin, V_i, we construct a subgraph $G_\tau \subset G$, where $G_\tau = (V_\tau, E_\tau)$. τ is a bin (the max bin of nodes and edges in G_τ). That is, G_τ consists of nodes, V_τ, and edges, E_τ, where V_τ are the documents in bin τ, and E_τ are citations from papers in V_τ to papers in $V_{i\leq\tau}$. In other words, we allow citations from papers in the current bin (bin τ) to papers in the current bin or in previous bins.

With this partitioning we may set the train-test splits to be between any two subsequent bins. Firstly, this allows us to adjust the size of the training graph to study the effects of scale. Secondly, it allows us to associate test predictions with a time bin. This allows for analysis of test performance as a forecasting task with a forecasting horizon of h. That is, if we train a model on bins up to t, how does the performance of the model on bin $t + 1$ compare with the performance on bin $t + 5$? In general, the task becomes more difficult with larger horizons h.

Let $G^{(\tau)}$ be a cumulative graph:

$$G^{(\tau)} = \sum_{i=0}^{\tau} G_i \qquad (1)$$

That is $G^{(\tau)} = (V_{i\leq\tau}, E_{i\leq\tau})$, where $V_{i\leq\tau}$ are documents in the current bin or previous bins, and $E_{i\leq\tau}$ are citations from these papers to papers in the current bin or previous bins.

Thus, $G^{(\tau)}$ is the union of all single-bin subgraphs graphs up to and including G_τ. We will

[8] In fact, there are many missing values (and incorrect values). The set of papers, V, is limited to papers with (non-missing) publication dates.

refer to the vertices and edges in $G^{(\tau)}$ as $V^{(\tau)}$ and $E^{(\tau)}$, respectively.

3.3 Distance of 4-hop Papers

Papers connected by 4 hops citation hops may appear unrelated. However, with a space of 200M papers, 4 hops is fairly close. It is very unlikely to move from one field to a completely different one in just 4 hops.

We have estimates of Field of Study (FOS) values for the pairs of papers (v_i, v_j) in the test set. FOS is tricky for a number of reasons, but some common FOS values are: Medicine, Biology and Computer Science. The priors for these FOS values are: 21%, 4.6% and 7.2%, respectively.

Pr(v_j is in medicine | v_i is in medicine) declines with hops: 68%, 65%, 62%, 58%. Pr(v_j is in biology | v_i is in biology) declines with hops: 38%, 30%, 22%, 17%. Pr(v_j is in CS | v_i is in CS) declines (less) with hops: 53%, 54%, 53%, 54%. Random negatives would mostly consist of papers in totally different fields, but our results show it is likely that papers separated by 4 hops are in the same field.

3.4 Dataset Balancing

Within our raw Citation Prediction dataset, we find a non-constant ratio of 1-hop to [2,4] hop labels across different bins. On average, 1-hop labels constitute 28.9%. The accuracy paradox (Valverde-Albacete and Peláez-Moreno, 2014) means that bins with a higher prevalence of [2,4] hops will be easier to obtain higher scores on. To rectify this, we down-sample the more-than-average prevalence class until the 28.9% rate is achieved. This adjustment results in the deletion of 7.6% samples. More details can be found in Appendix A. We report accuracy because it should be sufficient to use the same metric consistently for comparisons over time (bins).

3.5 Representation Models

We use our dataset to compare both node-text and edge-citation representation models.

Text: Specter is an academic document model designed to accept paper titles and abstracts as input. Specter is initialized to the SciBERT model (Beltagy et al., 2019), a variant of BERT trained through masked text denoising of academic documents. Specter is further trained to minimise a triplet loss across a query paper, a positive paper, and a negative paper. The positive paper is cited by the query, whilst the negative paper is not. The underlying training goal is to ensure the `[CLS]` token representation of the positive paper is closer (in L2 distance) than that of the negative paper. We use the more recent Specter2 model release.[9] Specter2 is trained over an approximately 2M paper portion of the S2 corpus. Figure 4 shows the distribution of Specter's training data across our time bins. Discounting the 0.7% of papers for which the publication date is unavailable, 99.8% of Specter2 training papers appear in bins [0-85], which span 1684-2019. We therefore call the Specter release Specter$^{(85)}$.

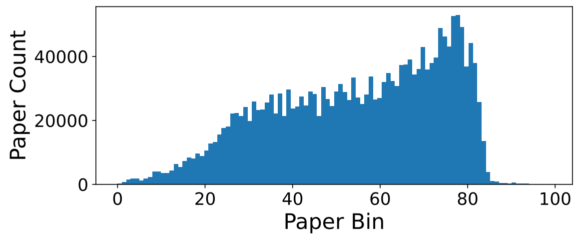

Figure 4: Histogram of $query$ papers by bin. Specter is trained on triples: $< query, pos, neg >$, where the $query$ paper cites the pos. The distribution of neg (random negatives) is similar to $query$, though pos predates $query$.

Citations: There are a number of methods such as Node2Vec (Grover and Leskovec, 2016), DeepWalk (Zhuoren et al., 2014) and ProNE (Zhang et al., 2019) that take the citation graph as input and apply techniques such as spectral clustering to return an embedding for each paper (vertex). As discussed in section 4.1.1. of (Cai et al., 2018), these methods produce embeddings where cosines can be interpreted in terms of the input graph. If two vectors have a large cosine, then the corresponding nodes are relatively close to one another in the input graph, though details depend on methods and hyperparameters.

We used the nodevector[10] implementation of ProNE to generate embeddings. We refer to the ProNE model trained on the S2 citation graph as: ProNE-S. In our experiments, the bottleneck is the SVD of the citation graph. Time and space requirements for SVD grow non-linearly with the size of the graph. Our SLURM cluster allows us to request 2 TBs of RAM and 5 days of runtime per job. The larger graphs consumed about half of these resources. We will need to replace the SVD with

[9] https://huggingface.co/allenai/specter2
[10] https://github.com/VHRanger/nodevectors

an approximation if the literature grows faster than our cluster.

ProNE is a transductive model, meaning it generates embeddings only for documents in the training set, but not for other documents. We introduce a *centroid* approximation to estimate vectors for other documents. The centroid approximation is:

$$vec(v_k) \approx \sum_{v_l \in fanout(v_k)} vec(v_l) \qquad (2)$$

where $vec(v)$ is the embedding for document v, and $fanout(v)$ is the set of papers that are reachable in one step from v (i.e. cited and citing papers). When evaluating ProNE-S embeddings, we prefer the original transductive embeddings and fallback with the centroid assumption when necessary.

We are interested evaluating two scaling effects:

1. The effect of graph scale on representation quality (size of τ)
2. The impact of time duration between train data and evaluation data (forecast horizon)

To evaluate these scaling effects, we train ProNE on each cumulative subgraph, $G^{(\tau)}, \tau \in [0, 99]$, resulting in 100 ProNE-S$^{(\tau)}$ models. ProNE-S$^{(\tau)}$ is trained on $G^{(\tau)}$, and maps documents in $V^{(\tau)}$ to vectors.

3.6 Evaluation Task

We evaluate both ProNE-S and Specter models on our Forecasting Citation Prediction dataset. Similar to cumulative graphs, we use the notation $M^{(\tau)}$ to indicate the maximum graph partition which a model is trained on. We report results for all bins, but like (Färber and Jatowt, 2020), we are particularly interested in predictions for papers published after the training set: bins $> \tau$. Results for bin $\leq \tau$ are less interesting because those bins were used for training.

As discussed in Section 1, we are interested in measuring trends in forecasting capability: how does accuracy depend on the interval between training time and evaluation time? Consistent with research in other domains (and common sense), we expect the task to become more challenging when the evaluation is based on papers that are published well after the papers in the training split.

3.7 Evaluation Implementation

We perform classification by taking the cosine similarity of model's representations of papers A and B

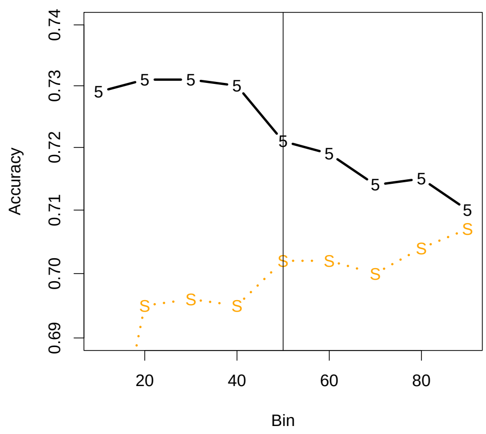

Figure 5: Results on ProNE-S$^{(50)}$ (trained on $G^{(50)}$) and tested on $T^{(k)}$ for $k \in \{10, 20, 30, 40, 50, 60, 70, 80, 90\}$; dashed lines compare with Specter.

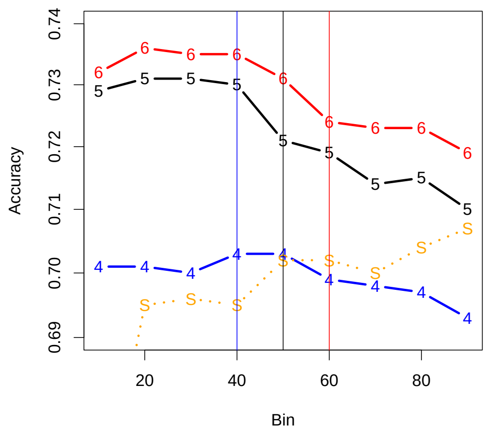

Figure 6: Performance improves with larger training sets: ProNE-S$^{(60)}$ $>$ ProNE-S$^{(50)}$ $>$ ProNE-S$^{(40)}$

and evaluating against a learn-able threshold. For each model, we use the first 1/6$^{\text{th}}$ of the data as a validation split to find this threshold, and evaluate on the remaining 5/6$^{\text{th}}$ of papers.

Missing Values: In the case of missing values for either paper, we predict by sampling from a Bernoulli distribution parameterised by the train distribution of the overall rate of 1 vs [2,4] hops (28.9%).

4 Results and Analysis

Figure 5 shows the performance of ProNE-S^{50} (labeled '5') on every tenth evaluation bin. Accuracy is better over the training set (left of the verticle line). Accuracy suddenly decreases moving into the first forecasting bin (h=1) and then slowly decreases further into the future. These results confirm our Forecast Dynamics assumption, that as time into the future increases, the model's performance degrades. We plot the Specter$^{(85)}$ (labeled 'S') for comparison. Despite having more recent training data, Specter underperforms ProNE-S$^{(50)}$.

Figure 6 is like Figure 5, but Figure 6 shows performance of three ProNE-S models, trained on ProNE-S$^{(40)}$ (blue/4), ProNE-S$^{(50)}$ (black/5) and ProNE-S$^{(40)}$ (red/6), respectively. Note that the red line is consistently above the black line, and the black line is consistently above the blue line (ProNE-S$^{(60)}$ > ProNE-S$^{(50)}$ > ProNE-S$^{(40)}$) because training on more bins is better than training on fewer bins. Figures 5-6 show that accuracy is better when tested on the training set, and declines the more we predict into the future.

Figures 5-6 are based on Table 2, which reports results for every tenth ProNE-S model and for Specter$^{(85)}$ in Table 2. These expanded results confirm the two results of note for ProNE-S model:

1. Accuracy degrades with h (forecast horizon), as shown in Figure 7. This observation is validated by OLS regression analysis, where accuracy drops by 0.0009 (coefficient: -0.0009, t-value: -41.246, p-value: <0.0001).
2. Accuracy improves with t (size of training set). For every additional training bin, accuracy improves by 0.0009 (coefficient: 0.0009, t-value: 12.280, p-value: <0.0001). This supports the use of very large training graphs.

Appendix B shows the full results for all cumulative 100 ProNE-S models and results on each 100 evaluation bins.

4.1 Early and Late Bins

Early bins (Bins 0-5) and late bins (Bins 95-99) produce outliers in our evaluation with both Specter and ProNE-S models, although the effect is most noticeable with Specter. We speculate that two effects are in play: (1) Specter's training set is skewed towards more recent papers (see Figure 4) and (2) older papers and newer papers have relatively noisy metadata due to issues such as OCR noise and preprints. OCR is more common for older papers and preprints are more common for newer papers.

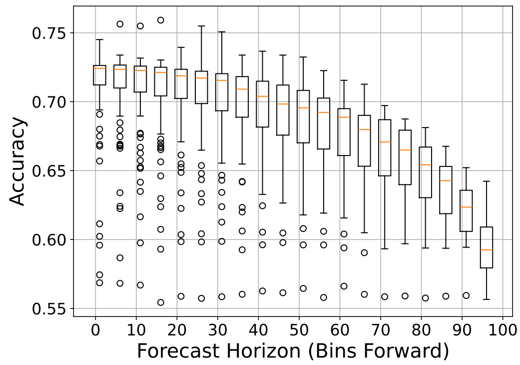

Figure 7: ProNE-S Accuracy Across Forecast Horizons

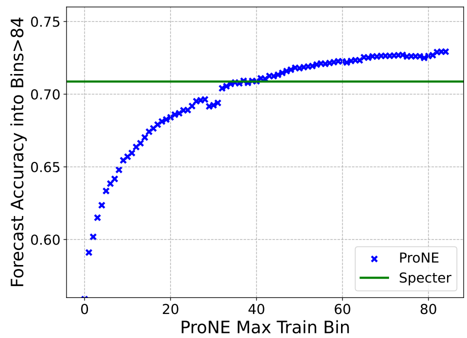

Figure 8: ProNE-S–Specter Crossover: Metcalfe's Law favors larger citation graphs (more than 82M papers).

4.2 Comparisons and Combinations

The next two subsections will discuss:

1. **Comparisons**: As suggested above, larger t (training data) favors ProNE-S, but where is the cross-over point?
2. **Combinations**: Ensembles of ProNE-S and Specter can be better than either by itself.

4.2.1 Comparing Text and Context (Citations)

As previously discussed, we train 100 ProNE-S models times on increasing cumulative graphs from G^0 to G^{99}. There is only a single Specter model, trained by S2 on papers published up to 2019, corresponding to our bin 85.[11] In Table 2 ProNE-S overtakes Specter at around bin 40, but it is not possible to make a precise determination from looking at every tenth bin.

According to our time binning, Specter2 is Specter$^{(85)}$, so we evaluate both ProNE-S and Specter on bins 86 to 99. For ProNE-S$^{(\tau)}$, we use all models where $\tau \leq 85$ as later iterations can access the test the citations during training. As we seek to compare models, we average the accuracy

[11] https://github.com/allenai/specter

ProNE-S Train Bins	Test Bin 0	10	20	30	40	50	60	70	80	90	Mean
0-0	0.543	0.573	0.557	0.559	0.566	0.563	0.561	0.562	0.561	0.558	0.560
0-10	0.701	0.706	0.662	0.670	0.663	0.663	0.665	0.659	0.659	0.659	0.663
0-20	0.736	0.724	0.725	0.709	0.703	0.700	0.698	0.693	0.690	0.686	0.699
0-30	0.701	0.701	0.701	0.700	0.703	0.703	0.699	0.698	0.697	0.693	0.703
0-40	0.751	0.729	0.731	0.731	0.730	0.721	0.719	0.714	0.715	0.710	0.724
0-50	0.772	0.732	0.736	0.735	0.735	0.731	0.724	0.723	0.723	0.719	0.733
0-60	0.756	0.732	0.732	0.736	0.735	0.734	0.732	0.726	0.724	0.725	0.738
0-70	0.726	0.726	0.733	0.734	0.734	0.735	0.735	0.737	0.726	0.730	0.743
0-80	0.731	0.732	0.736	0.736	0.737	0.733	0.734	0.735	0.733	0.730	0.745
0-90	0.736	0.731	0.737	0.733	0.736	0.736	0.735	0.740	0.739	0.740	0.750
Specter	0.569	0.661	0.695	0.696	0.695	0.702	0.702	0.700	0.704	0.707	0.701
Random Baseline	0.589	0.589	0.589	0.589	0.589	0.589	0.589	0.589	0.589	0.589	0.589

Table 2: Accuracy of 10 ProNE-S models and Specter on citation prediction forecasting task. Lines indicate the train-test divide.

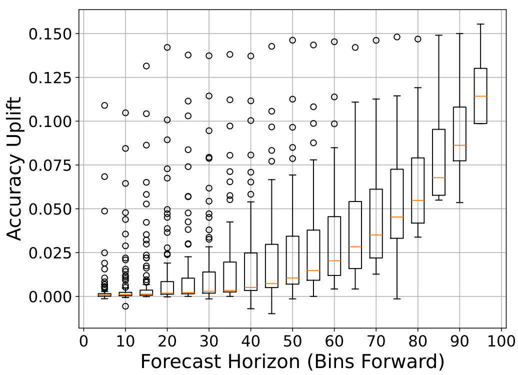

Figure 9: Hybrid Accuracy Uplift from ϕ_p to $\phi_{\frac{p}{s}}$ across all ProNE-S versions

over all forecasting bins rather that considering them individually. Figure 8 shows the averaged forecasting accuracy across for each model across bins 86 to 99. Specter outperforms the smaller ProNE-S models (left side of plot), whilst ProNE-S is better for larger graphs (right side of plot). The crossover point is around ProNE-S$^{(41)}$, which has about 82 million papers.

It is remarkable that ProNE-S$^{(41)}$ has comparable accuracy with Specter$^{(85)}$, given the large difference in t (training data). ProNE-S$^{(41)}$'s training data ends at bin 41 (2007), 11 years before the beginning of the test set (2018).

4.2.2 Combining Text and Context

We have evaluated the forecast capabilities of individual models and compared two different types of models, text and citation. A further area of evaluation is combining the predictions of the two different model types. Certain document representation models such as GNNs use both text and citations (nodes and edges) as input features. However, these methods may not apply to the case of missing values, which Figure 3 shows is more than half of S2. Additionally, we have shown that text- and citation-based models have different forecast characteristics. In a real world application, it may be desirable to optimise performance for papers published this year, given models trained on much older papers. This is somewhat equivalent to optimising for a particular evaluation bin. We show that under these conditions the optimal combination policy will change over time. To show this, we evaluate several strategies for ensembling Specter and ProNE-S models.

More formally: consider a scenario with N models M_i, each providing a forecast $F_i(t)$ at time t. The objective is to devise a combination policy ϕ that maximizes the forecast accuracy $A_i(t)$ for a given evaluation set. We will show that the optimal combination policy ϕ is not consistent across:

1. Different forecast horizons
2. Model variants with different train data (bins)

To make our study as clear as possible, we pick a straightforward hybrid system, which is to use ProNE-S citation embeddings when available, and otherwise, fall back to Specter text embeddings. We term this $\phi_{\frac{P_\tau}{S}}$, (where τ indicates the max train bin of the ProNE-S model). We run this policy across all ProNE-S$^{(\tau)}$ models, recording results as distances from the test-train split (i.e. for ProNE-S$^{(n)}$, predictions on bin $n+3$ count as a 3 bin forecast). Results are shown in Figure 9. This hybrid system improves performance, especially on extreme-range forecasting for the undertrained bin ProNE-S$^{(\tau)}$ models where $\tau < 40$.

In Section 4.2.1, we observed that the relative performance of ProNE-S and Specter depend on t (size of training set) and h (forecast horizon). We therefore compare $\phi_{\frac{P_\tau}{S}}$ to two 'no-op' baselines: (1) ProNE-S only: ϕ_{P_τ} and (2) Specter only: ϕ_S.

We evaluate all three policies on three ProNE-S variants: ProNE-S$^{(0)}$, ProNE-S$^{(10)}$, and ProNE-S$^{(30)}$. We choose these small τs to explore the region where Specter and ProNE-S have similar accuracy. The miss rate for for ProNE-S$^{(0)}$ is 89.5%, for ProNE-S$^{(10)}$ 40.0%, and for ProNE-S$^{(30)}$, it is 8.8%. We show that no single policy dominates over all forecasting horizons h. That is, there are regions where $\phi_{\frac{P_\tau}{S}}$ is best, and other regions where ϕ_{P_τ} is best, and regions where ϕ_S is best, as indicated by the color bars in Figure 10. The color bars also show that ensembling is often effective. Note that there is more green (ensembling) in Figure 10 than red (Specter only) and blue (ProNE-S only).

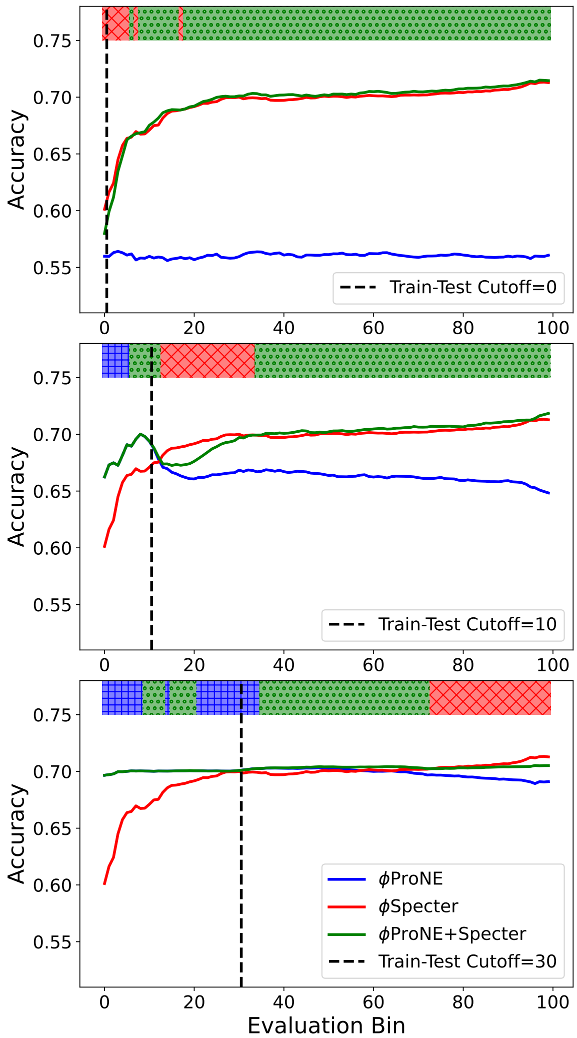

Figure 10: Hybrid Forecast Accuracy (with 5-point Moving Average) for $\phi_{\frac{P_\tau}{S}}$ with ProNE-S$^{(0),(10),(30)}$ and Specter. The color bars indicate which line has the best accuracy. Differences between bars suggest the policy for combining text and context depends on the size of the training set (t) and forecasting horizon (h).

We start with the least trained ProNE-S$^{(0)}$: $\phi_{\frac{P0}{S}}$. This ensemble uses ProNE-S when ProNE-S is able to form embeddings, and falls back to Specter otherwise. We plot the $\phi_{\frac{P0}{S}}$ vs ϕ_{P0} vs ϕ_S in the top plot of Figure 10. To highlight which ϕ is performing best at a given time-period, we shade above the graph the color of the best policy.

We observe that with ProNE-S$^{(0)}$, ϕ_S outperforms the hybrid system $\phi_{\frac{P0}{S}}$ for the first 8 bins, before converging for later forecast horizons. Convergence over latter bins is due to Specter dominating the hybrid system as ProNE-S has little coverage so far out from the training data. In $\phi_{\frac{P10}{S}}$ (middle plot) we see again that the under-trained ProNE-S system adds noise to short-range forecasts (bins 11-30), where ϕ_S – the Specter system alone – performs best. Finally the bottom plot of $\phi_{\frac{P30}{S}}$ shows that $\phi_{\frac{P30}{S}}$ becomes the optimal policy for forecasting near term (bins 31-70), whilst Specter remains more accurate for long range forecasting (bins 71-80). In short:

1. The optimal policy ϕ varies over models and time horizons. This can be seen through the color of best ϕ changing across each version of ProNE-S we plot in Figure 10.
2. By modelling Text and Citations separately, we are able to change the feature combination policy ϕ for different forecast horizons, which produces higher accuracy overall.

The hybrid system increases coverage from 96.0% to 99.0% for bin 50. We also find an uplift in prediction performance of 3.91% on average in forecasting bins, however, this varies by forecast distance and number of ProNE-S training bins. Further, we find that there is more opportunity for ensembling when there are more missing bins. Benefits for ensembling decrease when there is more training data.

5 Conclusion

We produced a link-prediction benchmark based on Semantic Scholar (S2) to measure forecasting capability of document models at scale. We then evaluated 100 ProNE-S models and Specter on data binned by time. Forecasting is important because science evolves over time. We found:

1. Performance improves as t increases (more training data over more time), and
2. Performance degrades as h increases (predictions further and further into the future).

Our results confirmed our central thesis: the time-evolving nature of Science requires that academic papers be modelled in a forecasting setting.

Metcalfe's Law suggests edge-based methods such as ProNE-S should be relatively effective for larger graphs. We found that was correct, with a cross-over point around 82 million papers, much larger than the training set for Specter.

Since ProNE is transductive (and does not generate embeddings for novel papers), we introduced the centroid assumption, so ProNE-S can generate embeddings for papers that cite known papers. This extended version of ProNE-S performed well on our forecasting benchmark, especially when trained on larger graphs.

We can interpret the forecasting horizon as a statement about how quickly ProNE embeddings go stale. Semantic Scholar creates Specter embeddings as papers are ingested. This is good practice because the text does not change after publication. It often takes time for the community to decide what is important. This means that for link-based methods like ProNE-S, citations will accrue on impactful papers over time, and therefore it is important to update ProNE embeddings frequently. Whilst this may be compute-expensive, our tests show that it leads to valuable increases in representational accuracy.

We further investigated the relationship of text and context models through an analysis of model combination strategies. First, we found that simply using Specter as a fallback for missing values in ProNE-S boosts long-horizon predictions significantly. Secondly, through evaluation over 100 cumulative ProNE-S models, we found the optimal model combination policy for combining Specter and ProNE-S depends on forecast horizon, h.

In practical applications, $h \gg 0$, since we typically train models once, and then use them much later for inference. Retraining more often will reduce h, and improve predictions at inference time. If we plan to combine models such as Specter and ProNE-S, the combination should be reevaluated more often since combinations also depend on h.

Finally, we will make our benchmark, embeddings and scripts available for further research and experimentation.

References

Z. Ali, Pavlos Kefalas, Khan Muhammad, Bahadar Ali, and Muhammad Imran. 2020. Deep learning in citation recommendation models survey. *Expert Syst. Appl.*, 162:113790.

Waleed Ammar, Dirk Groeneveld, Chandra Bhagavatula, Iz Beltagy, Miles Crawford, Doug Downey, Jason Dunkelberger, Ahmed Elgohary, Sergey Feldman, Vu Ha, Rodney Kinney, Sebastian Kohlmeier, Kyle Lo, Tyler Murray, Hsu Han Ooi, Matthew Peters, Joanna Power, Sam Skjonsberg, Lucy Lu Wang, Chris Wilhelm, Zheng Yuan, Madeleine Van Zuylen, and Oren Etzioni. 2018. Construction of the literature graph in semantic scholar. *NAACL HLT 2018 - 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference*, 3:84–91.

Joeran Beel, Bela Gipp, Stefan Langer, and Corinna Breitinger. 2015. Research-paper recommender systems: a literature survey. *International Journal on Digital Libraries*, 17:305 – 338.

Iz Beltagy, Kyle Lo, and Arman Cohan. 2019. SciBERT: A pretrained language model for scientific text. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3615–3620, Hong Kong, China. Association for Computational Linguistics.

Steven Bethard and Dan Jurafsky. 2010. Who should i cite: learning literature search models from citation behavior. *Proceedings of the 19th ACM international conference on Information and knowledge management*.

Hongyun Cai, Vincent W Zheng, and Kevin Chen-Chuan Chang. 2018. A comprehensive survey of graph embedding: Problems, techniques, and applications. *IEEE transactions on knowledge and data engineering*, 30(9):1616–1637.

Cornelia Caragea, Adrian Silvescu, Prasenjit Mitra, and C Lee Giles. 2013. Can't see the forest for the trees? a citation recommendation system. In *Proceedings of the 13th ACM/IEEE-CS joint conference on Digital libraries*, pages 111–114.

Arman Cohan, Sergey Feldman, Iz Beltagy, Doug Downey, and Daniel Weld. 2020. SPECTER: Document-level representation learning using citation-informed transformers. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2270–2282, Online. Association for Computational Linguistics.

S. Dumais and J. Nielsen. 1992. Automating the assignment of submitted manuscripts to reviewers. pages 233–244.

Michael Färber and · Adam Jatowt. 2020. Citation recommendation: approaches and datasets. *International Journal on Digital Libraries*, 21:375–405.

Aditya Grover and Jure Leskovec. 2016. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 855–864.

David Hall, Daniel Jurafsky, and Christopher D. Manning. 2008. Studying the history of ideas using topic models. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 363–371, Honolulu, Hawaii. Association for Computational Linguistics.

Qi He, Daniel Kifer, J. Pei, P. Mitra, and C. Lee Giles. 2011. Citation recommendation without author supervision. pages 755–764.

Weihua Hu, Matthias Fey, Hongyu Ren, Maho Nakata, Yuxiao Dong, and Jure Leskovec. 2021. OGB-LSC: A large-scale challenge for machine learning on graphs. *arXiv preprint arXiv:2103.09430*.

Weihua Hu, Matthias Fey, Marinka Zitnik, Yuxiao Dong, Hongyu Ren, Bowen Liu, Michele Catasta, and Jure Leskovec. 2020. Open graph benchmark: Datasets for machine learning on graphs. *Advances in neural information processing systems*, 33:22118–22133.

Rodney Michael Kinney, Chloe Anastasiades, Russell Authur, Iz Beltagy, Jonathan Bragg, Alexandra Buraczynski, Isabel Cachola, Stefan Candra, Yoganand Chandrasekhar, Arman Cohan, Miles Crawford, Doug Downey, Jason Dunkelberger, Oren Etzioni, Rob Evans, Sergey Feldman, Joseph Gorney, David W. Graham, F.Q. Hu, Regan Huff, Daniel King, Sebastian Kohlmeier, Bailey Kuehl, Michael Langan, Daniel Lin, Haokun Liu, Kyle Lo, Jaron Lochner, Kelsey MacMillan, Tyler Murray, Christopher Newell, Smita R Rao, Shaurya Rohatgi, Paul L Sayre, Zejiang Shen, Amanpreet Singh, Luca Soldaini, Shivashankar Subramanian, A. Tanaka, Alex D Wade, Linda M. Wagner, Lucy Lu Wang, Christopher Wilhelm, Caroline Wu, Jiangjiang Yang, Angele Zamarron, Madeleine van Zuylen, and Daniel S. Weld. 2023. The semantic scholar open data platform. *ArXiv*, abs/2301.10140.

T S Kuhn. 1962. *The structure of scientific revolutions*. Chicago.

Yicong Liang and Lap-Kei Lee. 2023. A systematic review of citation recommendation over the past two decades. *International Journal on Semantic Web and Information Systems*.

Shutian Ma, Chengzhi Zhang, and Xiaozhong Liu. 2020. A review of citation recommendation: from textual content to enriched context. *Scientometrics*, 122:1445–1472.

Mark T. Maybury. 2006. Expert finding systems. `https://www.mitre.org/sites/default/files/pdf/06_1115.pdf`.

Bob Metcalfe. 2013. Metcalfe's law after 40 years of Ethernet. *Computer*, 46(12):26–31.

David Mimno and Andrew McCallum. 2007. Expertise modeling for matching papers with reviewers. In *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 500–509.

Malte Ostendorff, Nils Rethmeier, Isabelle Augenstein, Bela Gipp, and Georg Rehm. 2022. Neighborhood contrastive learning for scientific document representations with citation embeddings. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11670–11688, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Reshma S Pillai and LR Deepthi. 2022. A survey on citation recommendation system. In *2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT)*, pages 423–429. IEEE.

Paul Resnick and Hal R Varian. 1997. Recommender systems. *Communications of the ACM*, 40(3):56–58.

Dwaipayan Roy. 2017. An improved test collection and baselines for bibliographic citation recommendation. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 2271–2274.

F. Scarselli, M. Gori, A. Tsoi, M. Hagenbuchner, and G. Monfardini. 2009. The graph neural network model. *IEEE Transactions on Neural Networks*, 20:61–80.

Amanpreet Singh, Mike D ' Arcy, Arman Cohan, Doug Downey, and Sergey Feldman. 2022a. Scirepeval: A multi-format benchmark for scientific document representations.

Amanpreet Singh, Mike D'Arcy, Arman Cohan, Doug Downey, and Sergey Feldman. 2022b. SciRepEval: A multi-format benchmark for scientific document representations. *ArXiv*, abs/2211.13308.

Laura Steinert. 2017. Beyond similarity and accuracy - a new take on automating scientific paper recommendations. pages 1–161.

Lynn A Streeter and Karen E Lochbaum. 1988. Who knows: A system based on automatic representation of semantic structure. In *User-Oriented Content-Based Text and Image Handling*, pages 380–388.

Trevor Strohman, W. Bruce Croft, and David D. Jensen. 2007. Recommending citations for academic papers. pages 705–706.

Kazunari Sugiyama and Min-Yen Kan. 2013. Exploiting potential citation papers in scholarly paper recommendation. pages 153–162.

Yuancheng Tu, Nikhil Johri, Dan Roth, and Julia Hockenmaier. 2010. Citation author topic model in expert search. In *Coling 2010: Posters*, pages 1265–1273, Beijing, China. Coling 2010 Organizing Committee.

Francisco J. Valverde-Albacete and Carmen Peláez-Moreno. 2014. 100% classification accuracy considered harmful: The normalized information transfer factor explains the accuracy paradox. *PLOS ONE*, 9(1):1–10.

Alex D Wade. 2022. The semantic scholar academic graph (s2ag). *Companion Proceedings of the Web Conference 2022*.

Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and Philip S. Yu. 2019. A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32:4–24.

David Yarowsky and Radu Florian. 1999. Taking the load off the conference chairs-towards a digital paper-routing assistant. In *1999 Joint SIGDAT Conference on Empirical Methods in Natural Language Processing and Very Large Corpora*.

Michihiro Yasunaga, Jure Leskovec, and Percy Liang. 2022. LinkBERT: Pretraining language models with document links. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8003–8016, Dublin, Ireland. Association for Computational Linguistics.

Dawit Yimam-Seid and Alfred Kobsa. 2003. Expert-finding systems for organizations: Problem and domain analysis and the demoir approach. *Journal of Organizational Computing and Electronic Commerce*, 13(1):1–24.

Jie Zhang, Yuxiao Dong, Yan Wang, Jie Tang, and Ming Ding. 2019. ProNE: Fast and scalable network representation learning. In *IJCAI*, volume 19, pages 4278–4284.

Yu Zhang, Yan-Jun Shen, Xiusi Chen, Bowen Jin, and Jiawei Han. 2023. "why should i review this paper?" unifying semantic, topic, and citation factors for paper-reviewer matching. *ArXiv*, abs/2310.14483.

Jie Zhou, Ganqu Cui, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu, and Maosong Sun. 2018. Graph neural networks: A review of methods and applications. *ArXiv*, abs/1812.08434.

Jiang Zhuoren, Z. Xiaozhong Liu, and Liangcai Gao. 2014. Dynamic topic/citation influence modeling for chronological citation recommendation. *International Conference on Information and Knowledge Management, Proceedings*, 2014-November:15–18.

6 Ethics

It is good for society to make the scientific literature more accessible. There is no sensitive data in this work. All of data we use for creating our benchmark is freely available through Semantic Scholar. The Specter2 model is available on Huggingface. We make the ProNE-S and Specter embeddings available on Globus. We release our benchmark on our project GitHub along with our evaluation code. Both embeddings and code are available under the MIT license.

7 Limitations

Scientific literature is growing quickly, and our benchmark will need to be updated frequently to stay relevant. Training ProNE-S over a 200 million paper benchmark requires significant compute resources (2+ days on a 2TB RAM HPC machine). Citations are not recorded as accurately for non-English language papers. Specter will likely not perform well for non-English language text and abstracts.

8 Acknowledgements

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A Semantic Scholar Dataset Details

Forecasting Dataset						ProNE Model	
Bin	Start Date	End Date	Original Count	Downsampled Count	% Decrease	Fail Count	Fail %
0	1684	1936	454	197	56.6	2,419,203	89.5
1	1936	1951	1,151	578	49.8	2,193,380	81.2
2	1951	1958	1,516	860	43.3	2,035,222	75.3
3	1958	1963	2,633	1,667	36.7	1,876,529	69.4
4	1963	1967	3,407	2,279	33.1	1,734,135	64.2
5	1967	1970	4,128	2,936	28.9	1,562,158	57.8
6	1970	1973	4,867	3,527	27.5	1,461,287	54.1
7	1973	1975	5,871	4,416	24.8	1,353,642	50.1
8	1975	1977	6,539	5,027	23.1	1,255,465	46.5
9	1977	1979	7,726	6,060	21.6	1,165,521	43.1
10	1979	1981	8,208	6,472	21.2	1,081,511	40.0
11	1981	1983	8,757	6,941	20.7	1,003,060	37.1
12	1983	1985	9,969	8,160	18.1	927,176	34.3
13	1985	1986	10,294	8,534	17.1	854,632	31.6
14	1986	1988	10,617	8,887	16.3	794,130	29.4
15	1988	1989	11,379	9,531	16.2	733,060	27.1
16	1989	1990	11,611	9,774	15.8	681,124	25.2
17	1990	1991	12,346	10,474	15.2	633,310	23.4
18	1991	1992	12,884	11,000	14.6	587,658	21.7
19	1992	1993	13,316	11,379	14.5	544,058	20.1
20	1993	1994	13,446	11,548	14.1	500,427	18.5
21	1994	1995	13,997	12,073	13.7	460,182	17.0
22	1995	1996	14,154	12,208	13.7	422,597	15.6
23	1996	1997	14,755	12,809	13.2	390,196	14.4
24	1997	1998	15,897	13,872	12.7	361,044	13.4
25	1998	1999	16,662	14,598	12.4	334,995	12.4
26	1999	1999	17,428	15,388	11.7	312,854	11.6
27	1999	2000	17,011	15,124	11.1	289,131	10.7
28	2000	2001	18,310	16,294	11.0	268,771	9.9
29	2001	2001	17,791	15,938	10.4	253,151	9.4
30	2001	2002	18,532	16,516	10.9	237,334	8.8
31	2002	2003	19,933	18,166	8.9	225,091	8.3
32	2003	2003	20,744	18,944	8.7	212,557	7.9
33	2003	2004	20,569	18,829	8.5	202,405	7.5
34	2004	2004	22,216	20,368	8.3	192,516	7.1
35	2004	2004	22,546	20,676	8.3	184,742	6.8
36	2004	2005	23,210	21,577	7.0	175,438	6.5
37	2005	2005	22,599	20,971	7.2	168,781	6.2
38	2005	2006	23,215	21,697	6.5	161,479	6.0
39	2006	2006	23,488	21,993	6.4	155,117	5.7
40	2006	2007	23,099	21,834	5.5	149,562	5.5
41	2007	2007	25,534	23,984	6.1	143,849	5.3
42	2007	2007	24,691	23,251	5.8	139,425	5.2
43	2007	2008	25,408	24,058	5.3	134,521	5.0
44	2008	2008	25,368	24,118	4.9	129,939	4.8
45	2008	2008	26,116	24,998	4.3	126,347	4.7
46	2008	2009	26,637	25,363	4.8	122,235	4.5
47	2009	2009	26,239	25,173	4.1	118,711	4.4
48	2009	2009	27,432	26,487	3.4	116,002	4.3
49	2009	2010	26,436	25,240	4.5	112,735	4.2
50	2010	2010	29,089	28,190	3.1	109,860	4.1
51	2010	2010	28,448	27,580	3.1	107,415	4.0
52	2010	2011	27,327	26,328	3.7	105,268	3.9
53	2011	2011	30,112	29,152	3.2	102,324	3.8
54	2011	2011	30,110	29,120	3.3	100,182	3.7
55	2011	2011	30,586	29,686	2.9	98,422	3.6
56	2011	2012	30,308	29,438	2.9	96,325	3.6
57	2012	2012	32,541	31,773	2.4	94,120	3.5
58	2012	2012	32,860	32,316	1.7	92,535	3.4
59	2012	2012	31,917	31,328	1.8	91,091	3.4
60	2012	2013	35,368	34,668	2.0	89,395	3.3
61	2013	2013	34,955	34,649	0.9	87,771	3.2
62	2013	2013	34,558	34,150	1.2	86,474	3.2
63	2013	2013	33,974	33,710	0.8	85,391	3.2
64	2013	2014	36,367	36,007	1.0	83,723	3.1
65	2014	2014	37,318	37,133	0.5	82,415	3.0
66	2014	2014	36,722	36,470	0.7	81,303	3.0
67	2014	2014	34,965	34,897	0.2	80,381	3.0
68	2014	2015	36,606	36,534	0.2	79,018	2.9
69	2015	2015	38,458	38,420	0.1	77,995	2.9
70	2015	2015	38,334	37,726	1.6	77,132	2.9
71	2015	2015	37,790	37,235	1.5	76,270	2.8
72	2015	2016	37,982	37,649	0.9	75,335	2.8
73	2016	2016	40,526	39,246	3.2	74,323	2.8
74	2016	2016	39,246	38,193	2.7	73,478	2.7
75	2016	2016	39,601	37,846	4.4	72,727	2.7
76	2016	2017	39,236	37,676	4.0	72,000	2.7
77	2017	2017	45,948	43,788	4.7	71,070	2.6
78	2017	2017	45,424	42,994	5.3	70,352	2.6
79	2017	2017	45,843	43,233	5.7	69,719	2.6
80	2017	2018	43,625	41,088	5.8	69,059	2.6
81	2018	2018	49,446	46,016	6.9	68,235	2.5
82	2018	2018	47,481	44,144	7.0	66,954	2.5
83	2018	2018	49,762	45,450	8.7	66,057	2.4
84	2018	2019	47,720	44,289	7.2	65,219	2.4
85	2019	2019	52,560	48,348	8.0	64,380	2.4
86	2019	2019	52,484	47,284	9.9	63,709	2.4
87	2019	2019	52,271	47,955	8.3	63,032	2.3
88	2019	2020	50,812	45,662	10.1	62,374	2.3
89	2020	2020	58,612	51,942	11.4	61,593	2.3
90	2020	2020	59,743	53,253	10.9	60,846	2.3
91	2020	2020	67,974	59,331	12.7	60,148	2.2
92	2020	2021	58,129	50,821	12.6	59,563	2.2
93	2021	2021	71,804	61,438	14.4	58,770	2.2
94	2021	2021	63,805	54,481	14.6	58,214	2.2
95	2021	2021	64,953	55,225	15.0	57,729	2.1
96	2021	2022	61,768	51,154	17.2	57,318	2.1
97	2022	2022	34,191	28,173	17.6	56,980	2.1
98	2022	2022	2,699	2,403	11.0	56,658	2.1
99	2022	2023	733	710	3.1	55,666	2.1

Table 3: Counts by Bin for Forecasting Dataset and ProNE Cumulative Model

B ProNE-S Forecast Heatmap

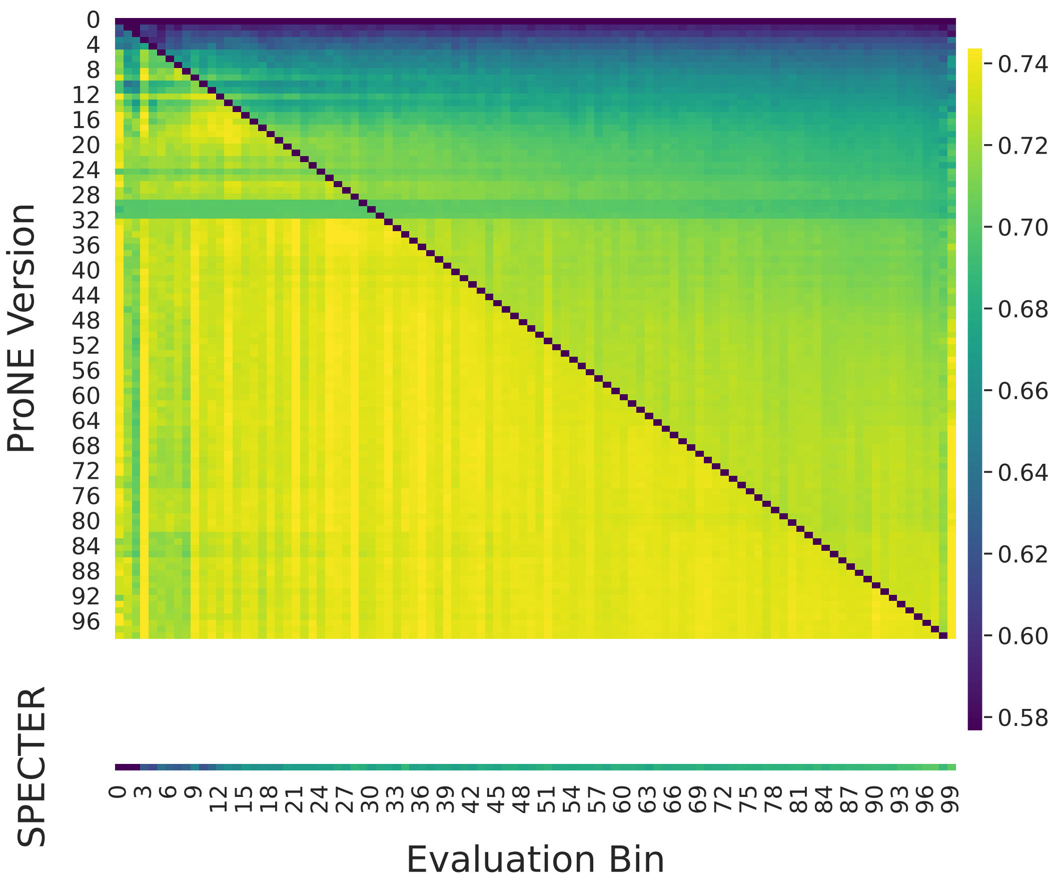

Figure 11: Full ProNE-S Cumulative Forecasting Results

C ProNE-S Forecast Table

Max Train Bin	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	0.548	0.574	0.557	0.559	0.577	0.554	0.568	0.547	0.565	0.550	0.563	0.567	0.555	0.557	0.554	0.559	0.554	0.562	0.559	0.559
1	0.624	0.606	0.569	0.613	0.604	0.583	0.598	0.587	0.601	0.601	0.597	0.595	0.598	0.599	0.603	0.593	0.592	0.593	0.593	0.596
2	0.614	0.640	0.664	0.602	0.605	0.593	0.610	0.607	0.622	0.615	0.610	0.616	0.614	0.616	0.611	0.618	0.610	0.603	0.607	0.604
3	0.655	0.647	0.652	0.664	0.596	0.597	0.621	0.614	0.629	0.624	0.623	0.626	0.623	0.637	0.635	0.631	0.627	0.616	0.621	0.624
4	0.645	0.638	0.657	0.674	0.651	0.611	0.624	0.620	0.631	0.635	0.634	0.648	0.628	0.635	0.640	0.642	0.639	0.631	0.621	0.627
5	0.716	0.671	0.677	0.720	0.701	0.696	0.657	0.654	0.663	0.676	0.668	0.666	0.657	0.663	0.662	0.653	0.657	0.650	0.646	0.646
6	0.711	0.664	0.683	0.719	0.702	0.704	0.701	0.669	0.658	0.682	0.666	0.676	0.668	0.667	0.664	0.661	0.664	0.652	0.657	0.647
7	0.716	0.671	0.673	0.713	0.699	0.700	0.700	0.713	0.668	0.679	0.667	0.678	0.673	0.675	0.668	0.666	0.666	0.671	0.653	0.658
8	0.711	0.685	0.678	0.739	0.706	0.716	0.711	0.731	0.715	0.697	0.679	0.690	0.684	0.685	0.685	0.675	0.684	0.679	0.671	0.674
9	0.736	0.697	0.691	0.747	0.718	0.714	0.721	0.730	0.721	0.743	0.696	0.706	0.695	0.698	0.697	0.690	0.686	0.684	0.679	0.682
10	0.695	0.642	0.650	0.705	0.682	0.684	0.686	0.697	0.698	0.714	0.706	0.675	0.676	0.667	0.668	0.669	0.669	0.660	0.660	0.659
11	0.695	0.666	0.658	0.704	0.688	0.693	0.701	0.701	0.702	0.715	0.711	0.720	0.680	0.679	0.682	0.678	0.675	0.668	0.669	0.666
12	0.756	0.709	0.699	0.732	0.717	0.724	0.724	0.723	0.729	0.735	0.736	0.738	0.739	0.709	0.708	0.700	0.700	0.694	0.693	0.689
13	0.721	0.694	0.669	0.713	0.677	0.703	0.698	0.701	0.702	0.714	0.715	0.720	0.724	0.722	0.691	0.681	0.678	0.677	0.676	0.669
14	0.726	0.709	0.685	0.730	0.691	0.705	0.709	0.706	0.710	0.722	0.725	0.725	0.732	0.730	0.728	0.694	0.685	0.685	0.683	0.678
15	0.751	0.723	0.703	0.743	0.709	0.717	0.714	0.717	0.720	0.732	0.733	0.738	0.736	0.737	0.736	0.726	0.699	0.693	0.699	0.693
16	0.797	0.709	0.720	0.735	0.703	0.711	0.717	0.718	0.721	0.731	0.729	0.737	0.734	0.740	0.728	0.727	0.726	0.698	0.701	0.696
17	0.777	0.704	0.719	0.745	0.716	0.718	0.726	0.725	0.730	0.736	0.733	0.740	0.737	0.741	0.739	0.734	0.728	0.730	0.714	0.709
18	0.777	0.711	0.703	0.738	0.717	0.725	0.729	0.727	0.732	0.738	0.736	0.737	0.739	0.742	0.738	0.735	0.732	0.731	0.733	0.710
19	0.741	0.723	0.717	0.730	0.723	0.727	0.723	0.725	0.729	0.733	0.732	0.729	0.732	0.740	0.740	0.730	0.727	0.728	0.731	0.729
20	0.731	0.723	0.719	0.725	0.724	0.728	0.718	0.725	0.723	0.730	0.724	0.724	0.725	0.734	0.732	0.722	0.726	0.724	0.728	0.724
21	0.736	0.718	0.719	0.726	0.723	0.729	0.719	0.721	0.722	0.729	0.724	0.724	0.721	0.734	0.732	0.722	0.726	0.725	0.727	0.724
22	0.736	0.716	0.716	0.713	0.719	0.721	0.719	0.715	0.717	0.722	0.716	0.721	0.714	0.723	0.721	0.716	0.719	0.717	0.722	0.716
23	0.741	0.718	0.714	0.716	0.720	0.721	0.719	0.718	0.719	0.727	0.719	0.720	0.717	0.728	0.727	0.719	0.722	0.719	0.722	0.718
24	0.701	0.706	0.706	0.702	0.707	0.711	0.709	0.705	0.708	0.711	0.708	0.710	0.706	0.713	0.709	0.708	0.711	0.709	0.711	0.710
25	0.736	0.713	0.713	0.714	0.717	0.720	0.715	0.714	0.717	0.724	0.717	0.720	0.715	0.722	0.720	0.717	0.719	0.718	0.721	0.719
26	0.746	0.715	0.716	0.728	0.724	0.722	0.722	0.730	0.727	0.730	0.728	0.725	0.723	0.736	0.737	0.729	0.727	0.728	0.731	0.732
27	0.726	0.708	0.716	0.728	0.728	0.721	0.724	0.726	0.723	0.729	0.725	0.724	0.720	0.733	0.734	0.724	0.727	0.724	0.727	0.726
28	0.726	0.718	0.713	0.722	0.720	0.721	0.722	0.721	0.722	0.724	0.719	0.721	0.720	0.728	0.727	0.721	0.722	0.723	0.724	0.722
29	0.701	0.699	0.699	0.699	0.700	0.700	0.701	0.700	0.701	0.700	0.701	0.700	0.700	0.700	0.701	0.701	0.700	0.701	0.701	0.701
30	0.690	0.701	0.699	0.699	0.700	0.700	0.701	0.701	0.701	0.700	0.701	0.700	0.700	0.700	0.701	0.701	0.700	0.701	0.701	0.701
31	0.701	0.701	0.700	0.699	0.701	0.702	0.701	0.701	0.701	0.701	0.701	0.701	0.701	0.702	0.702	0.701	0.701	0.701	0.702	0.702
32	0.736	0.728	0.721	0.734	0.725	0.727	0.726	0.728	0.725	0.738	0.733	0.732	0.736	0.740	0.737	0.731	0.734	0.733	0.741	0.735
33	0.746	0.727	0.719	0.732	0.725	0.725	0.724	0.727	0.725	0.737	0.735	0.731	0.733	0.741	0.737	0.732	0.735	0.732	0.742	0.735
34	0.746	0.720	0.730	0.733	0.724	0.725	0.723	0.731	0.724	0.739	0.737	0.731	0.732	0.741	0.739	0.731	0.735	0.732	0.743	0.733
35	0.761	0.718	0.717	0.738	0.729	0.726	0.721	0.731	0.726	0.738	0.737	0.730	0.736	0.743	0.739	0.734	0.734	0.730	0.742	0.734
36	0.761	0.709	0.712	0.737	0.727	0.729	0.726	0.731	0.724	0.741	0.733	0.730	0.733	0.741	0.738	0.730	0.735	0.732	0.739	0.732
37	0.766	0.721	0.707	0.738	0.729	0.728	0.729	0.731	0.730	0.743	0.735	0.730	0.733	0.740	0.737	0.732	0.733	0.733	0.740	0.730
38	0.741	0.711	0.710	0.737	0.731	0.728	0.724	0.731	0.729	0.740	0.730	0.727	0.729	0.737	0.737	0.729	0.733	0.731	0.737	0.729
39	0.756	0.709	0.710	0.733	0.729	0.728	0.729	0.732	0.728	0.740	0.731	0.727	0.732	0.736	0.735	0.729	0.732	0.733	0.736	0.729
40	0.751	0.713	0.717	0.742	0.729	0.728	0.728	0.731	0.730	0.739	0.729	0.727	0.729	0.735	0.733	0.728	0.732	0.732	0.733	0.728
41	0.772	0.716	0.706	0.740	0.727	0.727	0.723	0.732	0.728	0.745	0.731	0.730	0.731	0.738	0.735	0.731	0.732	0.733	0.738	0.729
42	0.761	0.718	0.712	0.741	0.727	0.731	0.727	0.731	0.731	0.739	0.730	0.727	0.729	0.738	0.732	0.730	0.734	0.733	0.736	0.730
43	0.761	0.716	0.710	0.738	0.725	0.729	0.725	0.732	0.727	0.742	0.730	0.729	0.729	0.742	0.736	0.733	0.732	0.732	0.740	0.731
44	0.766	0.721	0.714	0.738	0.725	0.728	0.730	0.735	0.730	0.741	0.729	0.730	0.731	0.740	0.735	0.732	0.733	0.734	0.739	0.728
45	0.756	0.720	0.709	0.738	0.727	0.726	0.724	0.735	0.728	0.742	0.732	0.730	0.730	0.739	0.734	0.733	0.732	0.734	0.738	0.731
46	0.772	0.706	0.712	0.743	0.728	0.723	0.726	0.728	0.727	0.741	0.731	0.730	0.731	0.740	0.735	0.732	0.732	0.733	0.740	0.731
47	0.756	0.718	0.707	0.741	0.731	0.729	0.721	0.732	0.725	0.742	0.731	0.730	0.731	0.739	0.736	0.734	0.733	0.734	0.740	0.731
48	0.772	0.720	0.702	0.738	0.728	0.725	0.722	0.728	0.719	0.742	0.732	0.730	0.733	0.742	0.734	0.732	0.733	0.733	0.740	0.731
49	0.766	0.718	0.707	0.739	0.728	0.726	0.720	0.727	0.723	0.741	0.733	0.729	0.731	0.743	0.733	0.733	0.734	0.734	0.739	0.730
50	0.766	0.718	0.705	0.741	0.733	0.722	0.723	0.730	0.724	0.741	0.732	0.728	0.730	0.742	0.733	0.732	0.735	0.731	0.738	0.730
51	0.756	0.718	0.697	0.741	0.730	0.726	0.720	0.728	0.723	0.741	0.735	0.730	0.731	0.743	0.732	0.733	0.732	0.732	0.740	0.731
52	0.746	0.715	0.700	0.745	0.731	0.724	0.720	0.728	0.719	0.744	0.731	0.732	0.731	0.743	0.733	0.732	0.735	0.732	0.739	0.730
53	0.746	0.718	0.703	0.743	0.728	0.728	0.729	0.730	0.722	0.743	0.733	0.732	0.733	0.744	0.732	0.732	0.736	0.732	0.739	0.731
54	0.772	0.718	0.709	0.743	0.724	0.725	0.720	0.730	0.719	0.742	0.731	0.735	0.731	0.741	0.733	0.732	0.732	0.732	0.739	0.731
55	0.761	0.716	0.710	0.747	0.727	0.725	0.723	0.729	0.718	0.742	0.730	0.733	0.731	0.743	0.729	0.732	0.734	0.730	0.737	0.732
56	0.751	0.725	0.703	0.747	0.728	0.724	0.722	0.728	0.719	0.740	0.732	0.732	0.732	0.742	0.731	0.732	0.735	0.731	0.738	0.732
57	0.751	0.718	0.703	0.744	0.731	0.726	0.720	0.726	0.719	0.743	0.730	0.733	0.731	0.741	0.732	0.732	0.736	0.731	0.736	0.730
58	0.756	0.727	0.710	0.747	0.728	0.729	0.724	0.728	0.719	0.741	0.731	0.734	0.735	0.740	0.732	0.732	0.734	0.730	0.738	0.731
59	0.761	0.715	0.702	0.744	0.728	0.722	0.720	0.728	0.715	0.741	0.731	0.731	0.733	0.741	0.732	0.732	0.734	0.731	0.738	0.730
60	0.751	0.723	0.705	0.747	0.726	0.721	0.721	0.726	0.715	0.742	0.732	0.732	0.732	0.740	0.732	0.733	0.736	0.730	0.737	0.731
61	0.741	0.723	0.698	0.741	0.727	0.731	0.727	0.727	0.725	0.742	0.732	0.737	0.733	0.741	0.735	0.736	0.736	0.732	0.738	0.732
62	0.751	0.720	0.700	0.743	0.730	0.722	0.725	0.727	0.722	0.741	0.731	0.738	0.735	0.741	0.735	0.735	0.734	0.733	0.737	0.729
63	0.741	0.718	0.703	0.747	0.733	0.727	0.722	0.728	0.723	0.741	0.731	0.737	0.734	0.743	0.735	0.735	0.734	0.733	0.737	0.732
64	0.741	0.718	0.698	0.744	0.732	0.730	0.724	0.729	0.724	0.738	0.732	0.736	0.734	0.743	0.732	0.736	0.736	0.735	0.738	0.730
65	0.746	0.721	0.702	0.744	0.728	0.721	0.722	0.726	0.717	0.740	0.730	0.734	0.736	0.742	0.731	0.734	0.735	0.732	0.736	0.731
66	0.741	0.720	0.702	0.747	0.728	0.722	0.722	0.728	0.717	0.740	0.729	0.733	0.735	0.741	0.731	0.734	0.735	0.730	0.737	0.732
67	0.746	0.725	0.705	0.743	0.723	0.718	0.720	0.723	0.714	0.739	0.730	0.730	0.734	0.740	0.731	0.736	0.736	0.730	0.735	0.731
68	0.746	0.720	0.705	0.752	0.729	0.718	0.720	0.726	0.716	0.740	0.730	0.735	0.735	0.740	0.730	0.736	0.737	0.730	0.735	0.733
69	0.746	0.728	0.700	0.746	0.725	0.717	0.719	0.723	0.714	0.741	0.728	0.733	0.734	0.743	0.731	0.734	0.735	0.731	0.735	0.731
70	0.736	0.720	0.703	0.745	0.721	0.718	0.718	0.723	0.714	0.738	0.727	0.731	0.734	0.742	0.729	0.733	0.736	0.730	0.735	0.731
71	0.756	0.725	0.701	0.750	0.727	0.722	0.719	0.725	0.717	0.738	0.727	0.730	0.735	0.740	0.730	0.733	0.735	0.732	0.735	0.730
72	0.746	0.725	0.700	0.750	0.725	0.721	0.718	0.725	0.714	0.741	0.728	0.734	0.736	0.741	0.730	0.733	0.737	0.730	0.736	0.731
73	0.726	0.720	0.703	0.746	0.718	0.721	0.719	0.724	0.715	0.740	0.728	0.732	0.734	0.740	0.729	0.734	0.736	0.729	0.737	0.732
74	0.726	0.713	0.703	0.741	0.719	0.721	0.720	0.721	0.711	0.739	0.728	0.731	0.734	0.739	0.728	0.733	0.736	0.729	0.734	0.731
75	0.741	0.727	0.703	0.744	0.729	0.725	0.727	0.726	0.723	0.741	0.730	0.736	0.735	0.739	0.733	0.737	0.738	0.732	0.738	0.730
76	0.751	0.723	0.710	0.748	0.729	0.728	0.726	0.729	0.724	0.741	0.732	0.736	0.735	0.740	0.733	0.737	0.738	0.733	0.737	0.733
77	0.741	0.732	0.702	0.746	0.727	0.724	0.730	0.726	0.723	0.741	0.730	0.738	0.734	0.740	0.734	0.739	0.738	0.731	0.739	0.732
78	0.736	0.728	0.701	0.747	0.728	0.726	0.727	0.726	0.723	0.740	0.731	0.738	0.735	0.740	0.734	0.737	0.736	0.731	0.738	0.732
79	0.731	0.727	0.710	0.743	0.731	0.727	0.732	0.728	0.728	0.740	0.731	0.737	0.734	0.738	0.735	0.737	0.735	0.732	0.739	0.730
80	0.731	0.728	0.705	0.743	0.728	0.728	0.734	0.727	0.725	0.740	0.732	0.740	0.735	0.738	0.734	0.738	0.737	0.732	0.740	0.732
81	0.736	0.727	0.709	0.752	0.727	0.728	0.731	0.726	0.724	0.740	0.732	0.737	0.736	0.739	0.735	0.737	0.737	0.730	0.739	0.730
82	0.736	0.720	0.706	0.743	0.715	0.715	0.719	0.715	0.713	0.738	0.726	0.727	0.729	0.735	0.727	0.732	0.735	0.727	0.733	0.727
83	0.716	0.720	0.702	0.741	0.720	0.715	0.716	0.725	0.713	0.739	0.725	0.730	0.732	0.736	0.726	0.734	0.734	0.727	0.736	0.727
84	0.726	0.723	0.707	0.748	0.717	0.717	0.720	0.718	0.711	0.736	0.724	0.727	0.729	0.734	0.726	0.730	0.733	0.726	0.735	0.728
85	0.721	0.713	0.699	0.745	0.713	0.714	0.720	0.718	0.706	0.734	0.724	0.727	0.730	0.733	0.726	0.729	0.732	0.726	0.733	0.727
86	0.731	0.739	0.714	0.744	0.724	0.722	0.723	0.723	0.717	0.740	0.731	0.734	0.735	0.738	0.728	0.736	0.737	0.728	0.737	0.730
87	0.736	0.732	0.708	0.747	0.722	0.724	0.719	0.720	0.719	0.741	0.730	0.732	0.736	0.737	0.731	0.736	0.737	0.730	0.738	0.731
88	0.741	0.732	0.707	0.746	0.720	0.721	0.723	0.721	0.714	0.740	0.728	0.734	0.732	0.737	0.729	0.735	0.736	0.726	0.740	0.731
89	0.731	0.735	0.716	0.741	0.718	0.720	0.721	0.722	0.717	0.739	0.730	0.733	0.732	0.736	0.727	0.734	0.735	0.728	0.737	0.730
90	0.731	0.734	0.709	0.751	0.724	0.720	0.720	0.721	0.719	0.741	0.731	0.735	0.732	0.737	0.730	0.735	0.738	0.729	0.736	0.730
91	0.731	0.732	0.715	0.751	0.717	0.723	0.718	0.723	0.715	0.740	0.731	0.734	0.728	0.735	0.727	0.734	0.734	0.723	0.735	0.730
92	0.711	0.728	0.727	0.756	0.724	0.720	0.718	0.723	0.718	0.742	0.731	0.735	0.728	0.737	0.728	0.736	0.736	0.725	0.735	0.731
93	0.741	0.728	0.722	0.752	0.720	0.724	0.717	0.722	0.718	0.742	0.730	0.735	0.731	0.736	0.729	0.733	0.736	0.726	0.734	0.730
94	0.726	0.730	0.719	0.754	0.720	0.724	0.718	0.720	0.720	0.741	0.732	0.737	0.730	0.738	0.727	0.737	0.736	0.728	0.737	0.733
95	0.746	0.723	0.719	0.744	0.721	0.721	0.718	0.721	0.715	0.739	0.729	0.731	0.729	0.731	0.728	0.735	0.735	0.725	0.738	0.731
96	0.746	0.734	0.720	0.754	0.726	0.722	0.724	0.720	0.720	0.742	0.735	0.740	0.731	0.737	0.731	0.738	0.737	0.730	0.738	0.733
97	0.726	0.728	0.726	0.756	0.724	0.718	0.724	0.720	0.721	0.742	0.734	0.739	0.733	0.737	0.731	0.737	0.737	0.728	0.737	0.731
98	0.736	0.728	0.717	0.752	0.723	0.722	0.727	0.720	0.722	0.740	0.734	0.742	0.732	0.740	0.733	0.739	0.736	0.728	0.739	0.734

Max Train Bin	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39
0	0.554	0.559	0.553	0.567	0.563	0.562	0.557	0.560	0.553	0.561	0.560	0.558	0.565	0.563	0.568	0.562	0.560	0.565	0.556	0.565
1	0.601	0.602	0.598	0.598	0.603	0.597	0.594	0.598	0.596	0.593	0.598	0.592	0.599	0.599	0.598	0.597	0.593	0.593	0.598	0.596
2	0.609	0.604	0.612	0.604	0.606	0.604	0.606	0.601	0.604	0.611	0.605	0.607	0.614	0.613	0.610	0.609	0.612	0.605	0.606	0.609
3	0.631	0.631	0.623	0.624	0.623	0.620	0.627	0.620	0.619	0.627	0.620	0.624	0.630	0.625	0.624	0.622	0.628	0.623	0.622	0.623
4	0.630	0.634	0.632	0.634	0.627	0.634	0.635	0.636	0.628	0.631	0.633	0.634	0.630	0.633	0.631	0.634	0.630	0.626	0.631	0.637
5	0.642	0.646	0.650	0.643	0.646	0.657	0.649	0.645	0.641	0.646	0.644	0.643	0.649	0.641	0.647	0.641	0.643	0.647	0.645	0.647
6	0.653	0.655	0.656	0.651	0.652	0.652	0.660	0.652	0.650	0.654	0.648	0.652	0.648	0.650	0.651	0.651	0.654	0.647	0.650	0.652
7	0.654	0.660	0.661	0.665	0.658	0.657	0.659	0.658	0.655	0.651	0.654	0.654	0.659	0.654	0.656	0.655	0.655	0.658	0.655	0.657
8	0.668	0.673	0.668	0.664	0.668	0.668	0.668	0.661	0.666	0.661	0.666	0.665	0.666	0.662	0.665	0.662	0.668	0.659	0.664	0.661
9	0.677	0.685	0.681	0.679	0.676	0.677	0.679	0.675	0.676	0.669	0.674	0.673	0.677	0.666	0.673	0.670	0.675	0.672	0.669	0.669
10	0.663	0.663	0.659	0.667	0.658	0.668	0.670	0.659	0.670	0.661	0.670	0.671	0.671	0.664	0.668	0.668	0.665	0.673	0.670	0.665
11	0.669	0.673	0.667	0.666	0.668	0.672	0.670	0.667	0.672	0.669	0.676	0.673	0.673	0.670	0.674	0.667	0.671	0.674	0.673	0.671
12	0.696	0.697	0.687	0.690	0.687	0.688	0.687	0.685	0.688	0.680	0.686	0.691	0.686	0.681	0.686	0.682	0.684	0.685	0.685	0.680
13	0.672	0.673	0.673	0.676	0.677	0.680	0.678	0.675	0.677	0.673	0.678	0.681	0.679	0.677	0.679	0.678	0.682	0.681	0.681	0.675
14	0.679	0.684	0.677	0.681	0.684	0.690	0.685	0.682	0.685	0.679	0.683	0.682	0.687	0.681	0.687	0.684	0.689	0.686	0.685	0.683
15	0.694	0.697	0.690	0.692	0.696	0.697	0.694	0.693	0.697	0.688	0.688	0.691	0.697	0.688	0.693	0.694	0.693	0.691	0.693	0.689
16	0.697	0.700	0.691	0.697	0.697	0.697	0.699	0.694	0.702	0.692	0.692	0.696	0.700	0.697	0.693	0.695	0.697	0.693	0.691	0.693
17	0.708	0.709	0.699	0.706	0.707	0.707	0.707	0.703	0.707	0.702	0.698	0.700	0.705	0.701	0.702	0.702	0.706	0.700	0.699	0.700
18	0.712	0.712	0.703	0.707	0.708	0.713	0.709	0.705	0.708	0.702	0.705	0.703	0.708	0.702	0.701	0.707	0.705	0.704	0.699	0.704
19	0.716	0.717	0.712	0.717	0.715	0.715	0.712	0.713	0.715	0.709	0.707	0.708	0.711	0.706	0.707	0.708	0.706	0.707	0.705	0.705
20	0.725	0.716	0.712	0.712	0.716	0.716	0.713	0.711	0.714	0.711	0.709	0.707	0.712	0.707	0.708	0.709	0.709	0.709	0.706	0.706
21	0.726	0.725	0.711	0.711	0.711	0.714	0.713	0.712	0.716	0.711	0.709	0.709	0.712	0.709	0.709	0.711	0.709	0.710	0.707	0.709
22	0.719	0.718	0.715	0.711	0.709	0.714	0.710	0.711	0.713	0.711	0.708	0.711	0.712	0.709	0.710	0.707	0.709	0.711	0.708	0.709
23	0.722	0.723	0.718	0.717	0.710	0.716	0.713	0.713	0.716	0.713	0.711	0.711	0.712	0.710	0.710	0.709	0.711	0.711	0.709	0.711
24	0.712	0.712	0.708	0.710	0.710	0.709	0.707	0.708	0.710	0.707	0.705	0.709	0.709	0.706	0.708	0.707	0.707	0.708	0.708	0.706
25	0.719	0.721	0.717	0.717	0.715	0.722	0.713	0.712	0.716	0.711	0.711	0.709	0.712	0.711	0.711	0.710	0.712	0.711	0.711	0.711
26	0.730	0.731	0.724	0.726	0.724	0.733	0.729	0.718	0.722	0.718	0.713	0.715	0.718	0.716	0.718	0.716	0.717	0.716	0.716	0.715
27	0.728	0.729	0.721	0.724	0.722	0.730	0.725	0.725	0.721	0.717	0.713	0.715	0.716	0.716	0.716	0.714	0.717	0.716	0.715	0.715
28	0.722	0.726	0.720	0.722	0.719	0.727	0.722	0.721	0.724	0.713	0.714	0.714	0.714	0.712	0.716	0.713	0.716	0.716	0.714	0.713
29	0.700	0.701	0.700	0.700	0.700	0.700	0.701	0.700	0.700	0.701	0.702	0.703	0.703	0.703	0.703	0.704	0.703	0.703	0.703	0.702
30	0.701	0.701	0.700	0.700	0.700	0.700	0.701	0.700	0.700	0.700	0.700	0.702	0.702	0.702	0.703	0.702	0.703	0.703	0.704	0.703
31	0.703	0.703	0.701	0.703	0.702	0.702	0.702	0.702	0.702	0.701	0.702	0.702	0.703	0.703	0.704	0.704	0.704	0.704	0.705	0.704
32	0.738	0.744	0.729	0.733	0.736	0.743	0.741	0.739	0.741	0.739	0.737	0.736	0.739	0.722	0.723	0.722	0.725	0.720	0.726	0.727
33	0.738	0.746	0.731	0.735	0.737	0.743	0.743	0.742	0.740	0.739	0.735	0.736	0.740	0.737	0.724	0.723	0.726	0.721	0.726	0.727
34	0.740	0.747	0.731	0.736	0.737	0.744	0.744	0.744	0.745	0.740	0.738	0.738	0.744	0.741	0.736	0.725	0.726	0.721	0.726	0.728
35	0.740	0.746	0.730	0.736	0.736	0.745	0.743	0.744	0.744	0.741	0.738	0.737	0.742	0.740	0.736	0.738	0.727	0.723	0.727	0.727
36	0.735	0.744	0.728	0.736	0.736	0.742	0.740	0.741	0.741	0.739	0.737	0.738	0.739	0.737	0.736	0.738	0.738	0.725	0.726	0.727
37	0.739	0.745	0.730	0.735	0.735	0.742	0.741	0.739	0.742	0.738	0.736	0.736	0.740	0.736	0.737	0.737	0.738	0.737	0.726	0.727
38	0.734	0.739	0.727	0.735	0.730	0.740	0.736	0.737	0.739	0.736	0.732	0.734	0.735	0.734	0.735	0.734	0.735	0.734	0.731	0.725
39	0.734	0.740	0.727	0.735	0.733	0.741	0.737	0.737	0.740	0.735	0.734	0.735	0.736	0.735	0.734	0.735	0.736	0.735	0.733	0.736
40	0.731	0.738	0.727	0.734	0.730	0.739	0.737	0.735	0.740	0.733	0.731	0.734	0.735	0.734	0.733	0.732	0.735	0.735	0.731	0.734
41	0.737	0.742	0.729	0.738	0.735	0.742	0.740	0.738	0.742	0.737	0.735	0.737	0.739	0.736	0.737	0.736	0.738	0.736	0.734	0.738
42	0.733	0.740	0.728	0.735	0.731	0.740	0.739	0.736	0.741	0.735	0.732	0.735	0.736	0.734	0.735	0.735	0.737	0.734	0.733	0.735
43	0.735	0.742	0.730	0.737	0.733	0.742	0.740	0.738	0.744	0.735	0.734	0.736	0.740	0.736	0.739	0.736	0.740	0.738	0.735	0.737
44	0.735	0.742	0.729	0.736	0.733	0.742	0.741	0.737	0.741	0.735	0.733	0.738	0.739	0.735	0.738	0.736	0.739	0.737	0.734	0.737
45	0.738	0.742	0.730	0.738	0.732	0.742	0.741	0.737	0.742	0.737	0.735	0.737	0.739	0.736	0.739	0.737	0.740	0.738	0.736	0.737
46	0.737	0.742	0.731	0.737	0.733	0.744	0.742	0.738	0.742	0.736	0.735	0.737	0.740	0.737	0.739	0.740	0.741	0.738	0.735	0.738
47	0.736	0.745	0.731	0.738	0.736	0.744	0.740	0.738	0.744	0.735	0.735	0.737	0.742	0.737	0.739	0.741	0.743	0.738	0.736	0.740
48	0.736	0.744	0.730	0.739	0.737	0.744	0.741	0.740	0.745	0.736	0.736	0.737	0.743	0.736	0.739	0.740	0.743	0.739	0.735	0.741
49	0.737	0.746	0.731	0.737	0.737	0.744	0.742	0.740	0.745	0.737	0.735	0.739	0.745	0.737	0.742	0.740	0.742	0.739	0.736	0.741
50	0.735	0.744	0.731	0.738	0.735	0.742	0.740	0.740	0.744	0.737	0.735	0.737	0.742	0.736	0.740	0.739	0.743	0.739	0.735	0.740
51	0.737	0.745	0.730	0.738	0.735	0.743	0.741	0.740	0.744	0.738	0.735	0.737	0.742	0.736	0.741	0.740	0.742	0.739	0.734	0.740
52	0.735	0.745	0.730	0.737	0.736	0.744	0.742	0.740	0.745	0.737	0.736	0.737	0.742	0.735	0.740	0.740	0.743	0.740	0.735	0.742
53	0.736	0.744	0.731	0.739	0.735	0.744	0.743	0.739	0.745	0.737	0.736	0.738	0.742	0.735	0.740	0.739	0.743	0.739	0.735	0.741
54	0.734	0.744	0.729	0.737	0.735	0.744	0.740	0.740	0.745	0.736	0.736	0.737	0.742	0.736	0.740	0.740	0.743	0.739	0.735	0.741
55	0.734	0.744	0.729	0.739	0.734	0.742	0.742	0.738	0.744	0.737	0.736	0.737	0.744	0.735	0.739	0.741	0.743	0.738	0.735	0.742
56	0.734	0.744	0.730	0.738	0.734	0.743	0.742	0.738	0.745	0.736	0.736	0.738	0.743	0.734	0.739	0.739	0.744	0.740	0.734	0.742
57	0.734	0.743	0.729	0.738	0.736	0.742	0.740	0.740	0.744	0.735	0.736	0.737	0.741	0.735	0.738	0.740	0.743	0.739	0.735	0.742
58	0.732	0.746	0.731	0.738	0.735	0.743	0.741	0.739	0.746	0.737	0.737	0.738	0.741	0.736	0.739	0.740	0.743	0.739	0.735	0.741
59	0.733	0.744	0.731	0.738	0.735	0.742	0.740	0.740	0.746	0.736	0.736	0.738	0.742	0.736	0.740	0.741	0.744	0.739	0.735	0.741
60	0.732	0.743	0.732	0.738	0.734	0.743	0.741	0.739	0.746	0.735	0.736	0.737	0.741	0.736	0.739	0.740	0.743	0.739	0.735	0.742
61	0.735	0.745	0.733	0.739	0.735	0.744	0.740	0.739	0.743	0.737	0.736	0.737	0.741	0.734	0.741	0.740	0.742	0.738	0.735	0.740
62	0.734	0.746	0.733	0.739	0.735	0.743	0.739	0.739	0.745	0.735	0.734	0.737	0.743	0.734	0.739	0.741	0.743	0.740	0.735	0.742
63	0.734	0.746	0.733	0.740	0.736	0.742	0.740	0.740	0.747	0.736	0.736	0.738	0.744	0.736	0.740	0.740	0.743	0.739	0.735	0.742
64	0.733	0.745	0.734	0.741	0.736	0.745	0.740	0.740	0.744	0.737	0.735	0.739	0.742	0.735	0.739	0.740	0.741	0.739	0.736	0.742
65	0.733	0.744	0.731	0.739	0.735	0.742	0.740	0.739	0.748	0.736	0.736	0.736	0.744	0.735	0.739	0.740	0.744	0.739	0.737	0.742
66	0.734	0.746	0.735	0.738	0.736	0.743	0.740	0.738	0.747	0.737	0.736	0.737	0.743	0.735	0.738	0.740	0.743	0.739	0.735	0.742
67	0.733	0.745	0.732	0.739	0.735	0.742	0.739	0.738	0.747	0.737	0.735	0.737	0.743	0.736	0.737	0.740	0.744	0.738	0.737	0.742
68	0.734	0.746	0.732	0.738	0.736	0.741	0.739	0.738	0.747	0.735	0.735	0.735	0.744	0.736	0.738	0.740	0.743	0.739	0.736	0.743
69	0.733	0.745	0.732	0.740	0.734	0.740	0.738	0.739	0.746	0.736	0.735	0.736	0.744	0.734	0.737	0.740	0.743	0.738	0.736	0.742
70	0.733	0.745	0.732	0.739	0.734	0.741	0.741	0.737	0.747	0.734	0.735	0.736	0.744	0.733	0.738	0.741	0.744	0.738	0.736	0.742
71	0.732	0.744	0.733	0.740	0.733	0.742	0.739	0.737	0.746	0.735	0.735	0.738	0.743	0.735	0.739	0.740	0.744	0.737	0.736	0.741
72	0.733	0.744	0.733	0.740	0.734	0.742	0.738	0.738	0.746	0.735	0.735	0.736	0.743	0.734	0.739	0.740	0.744	0.736	0.735	0.742
73	0.734	0.742	0.732	0.737	0.733	0.741	0.739	0.737	0.746	0.734	0.735	0.737	0.743	0.734	0.737	0.740	0.744	0.737	0.736	0.742
74	0.734	0.741	0.730	0.736	0.733	0.740	0.738	0.737	0.744	0.735	0.733	0.736	0.742	0.735	0.736	0.740	0.741	0.738	0.735	0.741
75	0.735	0.743	0.734	0.740	0.735	0.743	0.738	0.739	0.746	0.735	0.735	0.738	0.740	0.735	0.741	0.740	0.743	0.737	0.737	0.741
76	0.737	0.745	0.735	0.740	0.735	0.743	0.740	0.739	0.747	0.734	0.736	0.739	0.742	0.735	0.740	0.740	0.742	0.737	0.736	0.743
77	0.736	0.743	0.735	0.740	0.736	0.744	0.739	0.738	0.745	0.734	0.736	0.737	0.741	0.734	0.741	0.740	0.742	0.738	0.736	0.742
78	0.736	0.744	0.734	0.738	0.737	0.743	0.740	0.740	0.746	0.735	0.735	0.738	0.740	0.735	0.742	0.740	0.743	0.737	0.735	0.742
79	0.734	0.741	0.733	0.739	0.734	0.742	0.739	0.737	0.743	0.736	0.735	0.736	0.739	0.734	0.740	0.738	0.740	0.738	0.734	0.740
80	0.736	0.743	0.735	0.741	0.734	0.742	0.739	0.739	0.744	0.734	0.735	0.736	0.741	0.735	0.742	0.738	0.742	0.739	0.736	0.741
81	0.736	0.743	0.735	0.740	0.735	0.743	0.741	0.738	0.746	0.735	0.735	0.739	0.740	0.735	0.741	0.738	0.742	0.737	0.734	0.741
82	0.733	0.740	0.728	0.735	0.730	0.738	0.738	0.735	0.743	0.732	0.732	0.737	0.738	0.733	0.734	0.737	0.741	0.735	0.734	0.739
83	0.734	0.740	0.730	0.737	0.731	0.738	0.738	0.737	0.745	0.731	0.732	0.738	0.739	0.734	0.735	0.738	0.742	0.736	0.734	0.739
84	0.731	0.740	0.728	0.735	0.731	0.739	0.739	0.733	0.742	0.731	0.731	0.737	0.739	0.732	0.735	0.738	0.742	0.735	0.734	0.739
85	0.731	0.738	0.728	0.733	0.727	0.738	0.738	0.734	0.743	0.728	0.730	0.736	0.737	0.733	0.734	0.737	0.740	0.734	0.733	0.738
86	0.738	0.742	0.734	0.739	0.733	0.741	0.739	0.739	0.743	0.735	0.734	0.737	0.741	0.735	0.739	0.739	0.743	0.738	0.735	0.742
87	0.736	0.741	0.732	0.737	0.732	0.741	0.739	0.738	0.746	0.732	0.734	0.736	0.740	0.734	0.738	0.739	0.743	0.738	0.735	0.743
88	0.737	0.741	0.733	0.737	0.730	0.741	0.740	0.737	0.745	0.733	0.733	0.737	0.738	0.734	0.737	0.738	0.741	0.737	0.736	0.741
89	0.735	0.738	0.732	0.740	0.731	0.738	0.740	0.738	0.745	0.732	0.734	0.738	0.738	0.734	0.736	0.738	0.742	0.737	0.735	0.741
90	0.737	0.739	0.734	0.739	0.731	0.740	0.740	0.738	0.743	0.733	0.733	0.738	0.739	0.735	0.738	0.738	0.742	0.739	0.735	0.741
91	0.733	0.737	0.728	0.736	0.729	0.737	0.739	0.735	0.744	0.731	0.733	0.736	0.739	0.733	0.736	0.738	0.741	0.736	0.732	0.741
92	0.734	0.740	0.730	0.738	0.731	0.738	0.738	0.737	0.745	0.734	0.733	0.738	0.740	0.734	0.738	0.738	0.743	0.737	0.735	0.741
93	0.735	0.740	0.730	0.737	0.730	0.737	0.737	0.735	0.744	0.732	0.732	0.736	0.739	0.735	0.736	0.738	0.742	0.737	0.733	0.742
94	0.736	0.740	0.731	0.739	0.732	0.738	0.739	0.737	0.745	0.732	0.732	0.738	0.740	0.735	0.738	0.739	0.742	0.737	0.733	0.741
95	0.734	0.739	0.728	0.736	0.730	0.738	0.737	0.733	0.745	0.730	0.732	0.737	0.739	0.734	0.737	0.738	0.741	0.738	0.733	0.741
96	0.738	0.740	0.733	0.742	0.731	0.739	0.740	0.736	0.746	0.733	0.734	0.737	0.740	0.735	0.739	0.739	0.743	0.739	0.734	0.742
97	0.736	0.738	0.731	0.741	0.733	0.737	0.739	0.737	0.745	0.733	0.734	0.737	0.739	0.735	0.740	0.739	0.743	0.740	0.733	0.742
98	0.737	0.740	0.732	0.742	0.732	0.739	0.739	0.736	0.744	0.734	0.735	0.738	0.739	0.733	0.740	0.738	0.743	0.739	0.734	0.742

Max Train Bin	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59
0	0.566	0.563	0.555	0.559	0.563	0.557	0.561	0.564	0.559	0.562	0.557	0.565	0.564	0.563	0.562	0.560	0.558	0.563	0.565	0.557
1	0.592	0.595	0.596	0.596	0.597	0.593	0.601	0.598	0.599	0.591	0.599	0.595	0.596	0.598	0.593	0.590	0.598	0.596	0.592	0.594
2	0.602	0.606	0.606	0.605	0.606	0.603	0.613	0.610	0.605	0.605	0.608	0.607	0.609	0.608	0.607	0.604	0.607	0.608	0.606	0.611
3	0.620	0.627	0.617	0.625	0.624	0.620	0.625	0.621	0.617	0.626	0.621	0.622	0.618	0.622	0.618	0.619	0.619	0.618	0.619	0.619
4	0.620	0.631	0.625	0.634	0.634	0.633	0.632	0.628	0.626	0.629	0.630	0.629	0.632	0.632	0.626	0.631	0.630	0.628	0.630	0.630
5	0.638	0.642	0.637	0.643	0.643	0.642	0.647	0.640	0.639	0.638	0.643	0.639	0.638	0.644	0.641	0.640	0.641	0.640	0.640	0.639
6	0.647	0.650	0.642	0.653	0.646	0.648	0.651	0.646	0.643	0.644	0.648	0.647	0.644	0.648	0.643	0.647	0.647	0.645	0.646	0.646
7	0.646	0.660	0.649	0.655	0.650	0.653	0.654	0.650	0.649	0.651	0.647	0.653	0.652	0.652	0.649	0.654	0.654	0.646	0.652	0.651
8	0.657	0.660	0.656	0.665	0.659	0.657	0.666	0.656	0.657	0.657	0.658	0.659	0.655	0.656	0.656	0.658	0.658	0.655	0.656	0.654
9	0.671	0.670	0.667	0.668	0.670	0.667	0.668	0.666	0.665	0.670	0.662	0.663	0.662	0.662	0.663	0.663	0.668	0.660	0.663	0.659
10	0.664	0.669	0.667	0.667	0.668	0.667	0.668	0.665	0.661	0.666	0.666	0.665	0.661	0.663	0.659	0.665	0.665	0.663	0.664	0.664
11	0.667	0.670	0.668	0.671	0.670	0.666	0.674	0.669	0.664	0.670	0.672	0.667	0.666	0.670	0.664	0.665	0.667	0.663	0.669	0.670
12	0.678	0.681	0.679	0.683	0.676	0.678	0.684	0.676	0.676	0.673	0.676	0.674	0.675	0.675	0.669	0.674	0.676	0.671	0.673	0.678
13	0.673	0.677	0.675	0.680	0.673	0.677	0.680	0.673	0.672	0.674	0.675	0.675	0.677	0.673	0.670	0.674	0.676	0.670	0.672	0.675
14	0.683	0.681	0.682	0.682	0.679	0.683	0.686	0.676	0.680	0.681	0.682	0.678	0.679	0.676	0.671	0.679	0.684	0.673	0.677	0.680
15	0.688	0.692	0.689	0.690	0.687	0.688	0.692	0.687	0.686	0.689	0.689	0.688	0.687	0.684	0.679	0.683	0.689	0.680	0.685	0.681
16	0.691	0.692	0.690	0.692	0.687	0.692	0.692	0.687	0.686	0.688	0.689	0.688	0.689	0.688	0.683	0.686	0.692	0.684	0.686	0.686
17	0.696	0.697	0.697	0.694	0.696	0.694	0.696	0.695	0.693	0.693	0.696	0.693	0.692	0.693	0.689	0.692	0.696	0.687	0.693	0.692
18	0.700	0.698	0.699	0.699	0.698	0.699	0.699	0.697	0.698	0.695	0.695	0.695	0.695	0.696	0.692	0.693	0.697	0.689	0.694	0.694
19	0.703	0.704	0.703	0.700	0.701	0.702	0.702	0.700	0.700	0.698	0.699	0.699	0.697	0.697	0.695	0.697	0.698	0.695	0.695	0.697
20	0.703	0.706	0.704	0.702	0.702	0.703	0.704	0.702	0.699	0.700	0.700	0.701	0.698	0.698	0.699	0.698	0.696	0.697	0.696	0.700
21	0.705	0.705	0.707	0.703	0.704	0.704	0.705	0.703	0.705	0.700	0.703	0.703	0.700	0.699	0.701	0.700	0.698	0.700	0.699	0.699
22	0.706	0.705	0.707	0.704	0.703	0.703	0.706	0.703	0.704	0.703	0.703	0.702	0.700	0.700	0.700	0.700	0.701	0.701	0.699	0.699
23	0.707	0.708	0.709	0.707	0.708	0.706	0.707	0.706	0.706	0.705	0.706	0.704	0.705	0.701	0.701	0.702	0.701	0.703	0.702	0.702
24	0.705	0.706	0.707	0.705	0.705	0.702	0.706	0.705	0.704	0.704	0.705	0.703	0.703	0.701	0.700	0.702	0.700	0.702	0.701	0.701
25	0.709	0.711	0.710	0.708	0.707	0.705	0.708	0.708	0.707	0.704	0.706	0.706	0.705	0.705	0.704	0.703	0.703	0.706	0.704	0.704
26	0.714	0.714	0.713	0.714	0.712	0.712	0.713	0.712	0.711	0.710	0.709	0.711	0.710	0.708	0.704	0.708	0.710	0.708	0.707	0.706
27	0.713	0.714	0.714	0.714	0.713	0.713	0.713	0.712	0.711	0.711	0.709	0.712	0.710	0.710	0.707	0.709	0.710	0.708	0.706	0.705
28	0.713	0.714	0.714	0.714	0.711	0.712	0.713	0.710	0.709	0.710	0.708	0.711	0.710	0.710	0.705	0.710	0.709	0.708	0.707	0.706
29	0.703	0.702	0.703	0.703	0.703	0.702	0.703	0.702	0.702	0.701	0.703	0.701	0.701	0.703	0.700	0.701	0.701	0.701	0.701	0.701
30	0.703	0.703	0.702	0.703	0.703	0.702	0.703	0.703	0.703	0.703	0.703	0.701	0.703	0.702	0.702	0.701	0.701	0.702	0.701	0.701
31	0.704	0.704	0.703	0.705	0.706	0.704	0.705	0.704	0.704	0.705	0.704	0.703	0.705	0.703	0.703	0.703	0.702	0.703	0.703	0.703
32	0.719	0.721	0.722	0.720	0.715	0.722	0.722	0.718	0.716	0.718	0.719	0.722	0.719	0.718	0.716	0.718	0.716	0.714	0.716	0.713
33	0.720	0.721	0.723	0.722	0.714	0.721	0.722	0.719	0.718	0.719	0.719	0.723	0.719	0.719	0.718	0.717	0.719	0.714	0.718	0.714
34	0.721	0.722	0.723	0.723	0.716	0.723	0.724	0.720	0.719	0.721	0.719	0.724	0.720	0.722	0.719	0.718	0.719	0.718	0.718	0.716
35	0.721	0.722	0.725	0.723	0.716	0.725	0.724	0.721	0.719	0.721	0.720	0.725	0.719	0.719	0.720	0.717	0.720	0.717	0.720	0.715
36	0.721	0.723	0.725	0.724	0.716	0.726	0.724	0.719	0.720	0.721	0.720	0.726	0.720	0.720	0.720	0.719	0.722	0.718	0.720	0.716
37	0.725	0.725	0.726	0.724	0.717	0.726	0.723	0.720	0.721	0.721	0.722	0.727	0.720	0.720	0.719	0.720	0.721	0.718	0.722	0.717
38	0.722	0.722	0.724	0.724	0.717	0.724	0.723	0.722	0.721	0.719	0.720	0.726	0.719	0.719	0.718	0.721	0.721	0.718	0.719	0.717
39	0.723	0.725	0.724	0.724	0.717	0.726	0.722	0.721	0.722	0.719	0.721	0.726	0.720	0.722	0.720	0.720	0.721	0.716	0.720	0.718
40	0.730	0.724	0.722	0.724	0.718	0.725	0.721	0.719	0.721	0.720	0.720	0.725	0.719	0.719	0.719	0.720	0.722	0.717	0.721	0.718
41	0.733	0.736	0.725	0.725	0.719	0.726	0.724	0.722	0.723	0.720	0.723	0.729	0.719	0.722	0.720	0.722	0.722	0.719	0.722	0.719
42	0.731	0.733	0.734	0.725	0.720	0.725	0.722	0.721	0.722	0.722	0.722	0.727	0.720	0.722	0.720	0.721	0.723	0.719	0.722	0.718
43	0.733	0.738	0.736	0.735	0.720	0.725	0.723	0.723	0.724	0.721	0.723	0.729	0.721	0.723	0.722	0.724	0.724	0.718	0.723	0.720
44	0.733	0.737	0.736	0.735	0.730	0.723	0.723	0.721	0.723	0.721	0.723	0.729	0.722	0.723	0.722	0.723	0.725	0.718	0.722	0.720
45	0.733	0.737	0.736	0.735	0.730	0.733	0.723	0.722	0.724	0.722	0.723	0.730	0.720	0.723	0.723	0.725	0.725	0.720	0.723	0.721
46	0.735	0.738	0.737	0.736	0.731	0.734	0.733	0.723	0.724	0.723	0.725	0.730	0.722	0.724	0.722	0.723	0.725	0.720	0.723	0.721
47	0.736	0.739	0.737	0.736	0.733	0.736	0.735	0.734	0.723	0.722	0.725	0.732	0.723	0.725	0.724	0.724	0.725	0.720	0.724	0.720
48	0.736	0.740	0.739	0.738	0.733	0.737	0.736	0.736	0.735	0.724	0.724	0.731	0.725	0.725	0.723	0.723	0.726	0.720	0.724	0.722
49	0.735	0.740	0.740	0.738	0.733	0.738	0.736	0.736	0.736	0.734	0.723	0.731	0.724	0.726	0.724	0.723	0.726	0.721	0.724	0.722
50	0.735	0.740	0.738	0.738	0.734	0.737	0.735	0.735	0.736	0.735	0.731	0.729	0.724	0.726	0.724	0.724	0.726	0.722	0.723	0.723
51	0.735	0.739	0.738	0.738	0.733	0.736	0.736	0.735	0.735	0.735	0.731	0.738	0.724	0.727	0.725	0.724	0.729	0.721	0.724	0.724
52	0.735	0.739	0.739	0.738	0.734	0.738	0.737	0.735	0.735	0.734	0.732	0.739	0.735	0.727	0.724	0.725	0.727	0.721	0.725	0.725
53	0.735	0.740	0.739	0.738	0.734	0.737	0.737	0.735	0.735	0.735	0.731	0.738	0.733	0.732	0.724	0.725	0.727	0.720	0.725	0.725
54	0.735	0.741	0.740	0.739	0.735	0.739	0.737	0.736	0.736	0.735	0.733	0.738	0.735	0.734	0.733	0.724	0.728	0.721	0.725	0.724
55	0.735	0.740	0.740	0.739	0.735	0.738	0.737	0.736	0.736	0.735	0.733	0.738	0.735	0.734	0.734	0.733	0.728	0.722	0.725	0.726
56	0.734	0.740	0.739	0.739	0.735	0.738	0.737	0.736	0.735	0.736	0.733	0.740	0.735	0.733	0.733	0.734	0.735	0.722	0.726	0.726
57	0.735	0.739	0.739	0.740	0.735	0.740	0.737	0.736	0.735	0.737	0.732	0.738	0.734	0.735	0.734	0.734	0.736	0.731	0.725	0.727
58	0.735	0.738	0.740	0.740	0.735	0.739	0.737	0.736	0.735	0.737	0.734	0.738	0.736	0.735	0.735	0.734	0.737	0.730	0.733	0.725
59	0.734	0.739	0.740	0.741	0.735	0.740	0.736	0.738	0.735	0.738	0.734	0.741	0.735	0.735	0.735	0.736	0.736	0.732	0.735	0.735
60	0.735	0.739	0.739	0.741	0.735	0.740	0.738	0.739	0.736	0.736	0.734	0.740	0.735	0.736	0.735	0.734	0.736	0.732	0.733	0.734
61	0.735	0.739	0.737	0.738	0.736	0.738	0.737	0.737	0.736	0.737	0.732	0.740	0.735	0.734	0.734	0.735	0.737	0.732	0.733	0.734
62	0.735	0.740	0.740	0.739	0.735	0.739	0.737	0.737	0.737	0.737	0.733	0.740	0.735	0.735	0.735	0.736	0.738	0.732	0.733	0.733
63	0.735	0.740	0.739	0.739	0.736	0.739	0.738	0.737	0.736	0.738	0.733	0.741	0.736	0.736	0.736	0.736	0.737	0.733	0.735	0.735
64	0.734	0.740	0.740	0.740	0.735	0.738	0.737	0.737	0.736	0.738	0.733	0.740	0.735	0.735	0.735	0.735	0.738	0.732	0.734	0.734
65	0.736	0.740	0.740	0.741	0.734	0.740	0.738	0.740	0.736	0.737	0.734	0.741	0.736	0.737	0.735	0.737	0.739	0.732	0.735	0.735
66	0.737	0.740	0.739	0.741	0.734	0.738	0.737	0.739	0.736	0.736	0.733	0.742	0.736	0.737	0.735	0.737	0.739	0.733	0.734	0.736
67	0.734	0.741	0.740	0.742	0.734	0.739	0.738	0.740	0.737	0.737	0.735	0.741	0.738	0.737	0.736	0.736	0.739	0.732	0.735	0.736
68	0.735	0.741	0.741	0.742	0.734	0.740	0.738	0.739	0.737	0.737	0.735	0.742	0.736	0.737	0.735	0.737	0.738	0.733	0.735	0.737
69	0.736	0.739	0.741	0.742	0.734	0.740	0.739	0.739	0.736	0.738	0.735	0.742	0.736	0.738	0.735	0.737	0.738	0.733	0.735	0.737
70	0.734	0.740	0.739	0.741	0.734	0.739	0.738	0.738	0.736	0.737	0.735	0.741	0.736	0.737	0.736	0.738	0.739	0.734	0.736	0.738
71	0.735	0.740	0.741	0.742	0.733	0.739	0.739	0.738	0.737	0.737	0.735	0.741	0.737	0.737	0.735	0.736	0.739	0.732	0.736	0.736
72	0.734	0.740	0.739	0.741	0.733	0.739	0.738	0.739	0.737	0.738	0.735	0.741	0.735	0.738	0.735	0.736	0.738	0.734	0.736	0.737
73	0.733	0.739	0.740	0.741	0.733	0.739	0.737	0.738	0.736	0.737	0.735	0.741	0.736	0.737	0.735	0.736	0.738	0.734	0.736	0.737
74	0.733	0.739	0.739	0.741	0.732	0.740	0.737	0.737	0.735	0.738	0.736	0.741	0.736	0.738	0.735	0.735	0.739	0.734	0.735	0.738
75	0.737	0.738	0.739	0.740	0.735	0.739	0.737	0.738	0.736	0.739	0.734	0.741	0.736	0.736	0.735	0.736	0.737	0.733	0.735	0.734
76	0.736	0.738	0.739	0.740	0.735	0.739	0.738	0.738	0.737	0.739	0.734	0.741	0.738	0.735	0.735	0.736	0.738	0.733	0.735	0.735
77	0.737	0.738	0.738	0.739	0.735	0.740	0.738	0.737	0.737	0.739	0.735	0.741	0.737	0.736	0.736	0.735	0.738	0.734	0.736	0.734
78	0.736	0.738	0.739	0.739	0.735	0.739	0.736	0.738	0.737	0.739	0.735	0.741	0.737	0.735	0.735	0.736	0.738	0.733	0.736	0.735
79	0.736	0.737	0.736	0.739	0.734	0.738	0.734	0.737	0.734	0.739	0.732	0.740	0.736	0.734	0.734	0.735	0.736	0.733	0.733	0.733
80	0.737	0.737	0.738	0.739	0.735	0.739	0.735	0.739	0.736	0.739	0.734	0.742	0.737	0.735	0.734	0.736	0.737	0.733	0.736	0.734
81	0.737	0.738	0.740	0.740	0.735	0.740	0.736	0.738	0.735	0.739	0.734	0.741	0.736	0.736	0.734	0.735	0.738	0.734	0.736	0.735
82	0.733	0.735	0.738	0.739	0.730	0.737	0.735	0.738	0.735	0.736	0.736	0.741	0.735	0.737	0.735	0.735	0.739	0.734	0.735	0.736
83	0.734	0.736	0.738	0.741	0.732	0.739	0.735	0.738	0.736	0.737	0.736	0.740	0.736	0.737	0.733	0.736	0.739	0.734	0.734	0.736
84	0.732	0.734	0.738	0.738	0.730	0.736	0.735	0.736	0.736	0.736	0.736	0.740	0.735	0.737	0.734	0.735	0.739	0.734	0.734	0.736
85	0.732	0.734	0.736	0.737	0.730	0.737	0.734	0.736	0.735	0.735	0.735	0.739	0.735	0.736	0.734	0.735	0.738	0.734	0.733	0.735
86	0.735	0.737	0.738	0.740	0.735	0.738	0.737	0.739	0.739	0.739	0.737	0.742	0.736	0.737	0.736	0.736	0.739	0.733	0.734	0.737
87	0.735	0.737	0.739	0.741	0.733	0.739	0.737	0.740	0.738	0.737	0.736	0.741	0.737	0.736	0.736	0.736	0.739	0.734	0.735	0.736
88	0.734	0.737	0.738	0.740	0.734	0.738	0.736	0.739	0.738	0.738	0.736	0.741	0.737	0.737	0.735	0.736	0.739	0.735	0.735	0.737
89	0.736	0.738	0.739	0.741	0.733	0.738	0.736	0.738	0.737	0.738	0.736	0.740	0.736	0.737	0.735	0.736	0.738	0.735	0.734	0.736
90	0.736	0.738	0.739	0.741	0.733	0.739	0.736	0.740	0.738	0.739	0.736	0.741	0.738	0.738	0.735	0.736	0.738	0.735	0.735	0.736
91	0.735	0.736	0.738	0.739	0.732	0.738	0.734	0.737	0.737	0.738	0.737	0.740	0.735	0.738	0.734	0.736	0.738	0.734	0.734	0.734
92	0.736	0.737	0.739	0.741	0.733	0.738	0.735	0.739	0.739	0.740	0.737	0.740	0.737	0.737	0.736	0.737	0.738	0.735	0.735	0.736
93	0.735	0.736	0.738	0.740	0.732	0.738	0.734	0.738	0.738	0.738	0.738	0.741	0.736	0.737	0.735	0.737	0.739	0.735	0.733	0.735
94	0.736	0.738	0.738	0.742	0.735	0.738	0.735	0.740	0.737	0.740	0.738	0.741	0.737	0.737	0.736	0.737	0.738	0.735	0.734	0.735
95	0.734	0.736	0.736	0.738	0.731	0.738	0.734	0.737	0.737	0.738	0.737	0.741	0.735	0.737	0.734	0.736	0.739	0.734	0.734	0.735
96	0.737	0.737	0.738	0.742	0.735	0.739	0.735	0.739	0.739	0.741	0.738	0.742	0.737	0.737	0.737	0.736	0.739	0.735	0.735	0.737
97	0.736	0.738	0.738	0.742	0.734	0.739	0.736	0.738	0.738	0.740	0.738	0.742	0.738	0.737	0.736	0.737	0.738	0.735	0.735	0.735
98	0.737	0.738	0.738	0.740	0.735	0.738	0.736	0.738	0.738	0.740	0.737	0.742	0.737	0.737	0.735	0.738	0.738	0.736	0.735	0.736

Max Train Bin	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79
0	0.560	0.566	0.563	0.564	0.561	0.560	0.560	0.560	0.561	0.559	0.557	0.558	0.558	0.564	0.562	0.557	0.559	0.562	0.563	0.564
1	0.596	0.595	0.594	0.596	0.593	0.595	0.594	0.590	0.597	0.593	0.593	0.596	0.593	0.594	0.594	0.594	0.595	0.597	0.590	0.593
2	0.607	0.604	0.612	0.604	0.608	0.606	0.605	0.606	0.605	0.604	0.598	0.603	0.606	0.605	0.600	0.607	0.603	0.605	0.601	0.603
3	0.625	0.617	0.624	0.622	0.616	0.621	0.617	0.622	0.619	0.621	0.619	0.618	0.621	0.618	0.620	0.616	0.617	0.618	0.616	0.617
4	0.630	0.630	0.633	0.632	0.625	0.629	0.630	0.628	0.626	0.625	0.622	0.624	0.629	0.628	0.624	0.628	0.623	0.626	0.624	0.627
5	0.644	0.636	0.639	0.640	0.635	0.640	0.637	0.641	0.642	0.636	0.637	0.637	0.640	0.637	0.633	0.637	0.637	0.637	0.635	0.635
6	0.644	0.638	0.646	0.647	0.642	0.645	0.644	0.644	0.641	0.643	0.642	0.645	0.646	0.643	0.640	0.641	0.643	0.646	0.637	0.642
7	0.655	0.647	0.651	0.651	0.650	0.651	0.647	0.648	0.650	0.647	0.650	0.648	0.647	0.649	0.649	0.647	0.648	0.647	0.639	0.646
8	0.658	0.654	0.658	0.660	0.654	0.656	0.658	0.653	0.657	0.652	0.653	0.653	0.654	0.652	0.651	0.654	0.652	0.653	0.647	0.653
9	0.667	0.663	0.660	0.666	0.659	0.660	0.660	0.660	0.662	0.659	0.661	0.661	0.660	0.662	0.659	0.659	0.660	0.658	0.655	0.657
10	0.667	0.656	0.661	0.666	0.662	0.662	0.663	0.663	0.665	0.662	0.662	0.661	0.659	0.662	0.661	0.662	0.663	0.662	0.657	0.660
11	0.671	0.664	0.666	0.669	0.664	0.668	0.668	0.667	0.666	0.664	0.665	0.666	0.663	0.665	0.666	0.665	0.664	0.664	0.663	0.663
12	0.677	0.672	0.674	0.674	0.673	0.670	0.670	0.672	0.671	0.672	0.671	0.673	0.672	0.673	0.667	0.666	0.671	0.671	0.667	0.668
13	0.674	0.670	0.672	0.674	0.670	0.674	0.672	0.671	0.673	0.675	0.673	0.669	0.667	0.672	0.674	0.672	0.671	0.673	0.666	0.671
14	0.678	0.675	0.676	0.679	0.675	0.679	0.675	0.678	0.676	0.677	0.676	0.674	0.673	0.679	0.674	0.674	0.675	0.675	0.672	0.672
15	0.687	0.682	0.682	0.684	0.679	0.680	0.679	0.684	0.685	0.683	0.681	0.679	0.680	0.681	0.678	0.681	0.678	0.681	0.679	0.678
16	0.688	0.681	0.686	0.686	0.685	0.687	0.684	0.685	0.686	0.686	0.686	0.681	0.685	0.682	0.682	0.683	0.683	0.681	0.678	0.678
17	0.689	0.685	0.690	0.692	0.689	0.690	0.688	0.688	0.690	0.689	0.689	0.684	0.684	0.686	0.684	0.687	0.684	0.684	0.683	0.681
18	0.696	0.689	0.693	0.693	0.691	0.692	0.690	0.691	0.691	0.691	0.691	0.690	0.687	0.691	0.689	0.687	0.689	0.687	0.688	0.687
19	0.697	0.692	0.694	0.695	0.694	0.694	0.695	0.692	0.694	0.693	0.693	0.689	0.690	0.690	0.690	0.691	0.692	0.689	0.689	0.688
20	0.697	0.695	0.696	0.696	0.694	0.698	0.694	0.694	0.695	0.692	0.692	0.690	0.690	0.693	0.692	0.693	0.693	0.693	0.690	0.689
21	0.699	0.699	0.698	0.701	0.696	0.696	0.697	0.695	0.695	0.697	0.693	0.692	0.694	0.695	0.694	0.694	0.694	0.694	0.691	0.689
22	0.700	0.697	0.698	0.699	0.697	0.699	0.697	0.696	0.696	0.696	0.695	0.692	0.693	0.693	0.694	0.696	0.696	0.693	0.692	0.691
23	0.701	0.700	0.700	0.700	0.699	0.700	0.699	0.698	0.699	0.698	0.696	0.697	0.696	0.697	0.696	0.697	0.697	0.695	0.695	0.691
24	0.701	0.698	0.699	0.699	0.700	0.699	0.698	0.699	0.698	0.697	0.694	0.695	0.695	0.695	0.696	0.698	0.697	0.696	0.693	0.693
25	0.704	0.701	0.703	0.703	0.703	0.702	0.702	0.701	0.699	0.700	0.698	0.699	0.699	0.699	0.700	0.700	0.699	0.697	0.696	0.695
26	0.708	0.704	0.706	0.708	0.705	0.704	0.706	0.704	0.704	0.704	0.702	0.703	0.702	0.703	0.702	0.702	0.704	0.703	0.703	0.700
27	0.707	0.705	0.706	0.706	0.707	0.704	0.705	0.706	0.704	0.704	0.704	0.704	0.702	0.702	0.703	0.703	0.703	0.702	0.702	0.700
28	0.707	0.705	0.705	0.707	0.706	0.704	0.706	0.704	0.704	0.704	0.703	0.704	0.702	0.703	0.702	0.702	0.703	0.702	0.701	0.701
29	0.701	0.699	0.701	0.701	0.700	0.700	0.700	0.700	0.698	0.698	0.696	0.696	0.698	0.697	0.697	0.696	0.695	0.698	0.695	0.695
30	0.699	0.700	0.700	0.701	0.700	0.700	0.700	0.699	0.699	0.701	0.698	0.696	0.697	0.697	0.696	0.699	0.695	0.697	0.696	0.695
31	0.702	0.701	0.702	0.703	0.702	0.701	0.702	0.702	0.701	0.701	0.699	0.699	0.700	0.698	0.698	0.699	0.699	0.699	0.698	0.698
32	0.718	0.714	0.714	0.715	0.714	0.715	0.714	0.710	0.712	0.714	0.710	0.709	0.712	0.713	0.710	0.709	0.711	0.710	0.709	0.710
33	0.718	0.716	0.712	0.714	0.717	0.714	0.715	0.712	0.714	0.714	0.713	0.709	0.713	0.713	0.711	0.711	0.713	0.710	0.710	0.709
34	0.719	0.719	0.715	0.717	0.719	0.717	0.718	0.712	0.714	0.715	0.713	0.713	0.714	0.715	0.713	0.714	0.713	0.710	0.712	0.712
35	0.720	0.719	0.715	0.716	0.717	0.716	0.718	0.714	0.717	0.717	0.714	0.714	0.718	0.717	0.711	0.714	0.716	0.710	0.712	0.712
36	0.718	0.717	0.715	0.717	0.718	0.717	0.718	0.713	0.716	0.718	0.713	0.714	0.718	0.715	0.713	0.714	0.715	0.712	0.711	0.712
37	0.720	0.719	0.718	0.718	0.720	0.718	0.719	0.715	0.717	0.718	0.714	0.714	0.718	0.718	0.713	0.715	0.716	0.713	0.713	0.714
38	0.719	0.717	0.716	0.716	0.718	0.715	0.720	0.714	0.716	0.717	0.712	0.715	0.717	0.715	0.713	0.712	0.716	0.713	0.711	0.713
39	0.720	0.717	0.718	0.718	0.719	0.717	0.719	0.716	0.717	0.719	0.714	0.716	0.718	0.717	0.715	0.713	0.716	0.714	0.713	0.714
40	0.719	0.716	0.717	0.717	0.718	0.716	0.721	0.715	0.717	0.717	0.713	0.716	0.715	0.718	0.715	0.713	0.717	0.712	0.713	0.712
41	0.721	0.719	0.719	0.721	0.721	0.720	0.721	0.716	0.719	0.721	0.716	0.717	0.720	0.720	0.716	0.715	0.719	0.714	0.715	0.716
42	0.721	0.719	0.720	0.719	0.719	0.718	0.722	0.716	0.717	0.719	0.715	0.717	0.720	0.719	0.716	0.714	0.719	0.714	0.716	0.715
43	0.722	0.722	0.720	0.722	0.721	0.721	0.723	0.716	0.719	0.722	0.717	0.718	0.719	0.719	0.718	0.717	0.719	0.716	0.717	0.716
44	0.721	0.720	0.720	0.722	0.721	0.721	0.723	0.716	0.718	0.722	0.717	0.719	0.721	0.720	0.718	0.715	0.721	0.715	0.717	0.717
45	0.722	0.722	0.722	0.723	0.722	0.720	0.724	0.718	0.719	0.723	0.719	0.720	0.722	0.721	0.719	0.717	0.720	0.717	0.718	0.717
46	0.722	0.721	0.722	0.723	0.723	0.722	0.723	0.719	0.720	0.723	0.718	0.721	0.721	0.721	0.719	0.717	0.721	0.717	0.718	0.718
47	0.721	0.723	0.722	0.725	0.723	0.721	0.725	0.719	0.721	0.725	0.720	0.721	0.722	0.721	0.721	0.719	0.721	0.719	0.720	0.720
48	0.724	0.722	0.723	0.726	0.725	0.722	0.726	0.722	0.722	0.726	0.720	0.722	0.724	0.723	0.722	0.719	0.722	0.719	0.720	0.720
49	0.725	0.724	0.722	0.727	0.726	0.724	0.725	0.722	0.722	0.726	0.722	0.723	0.725	0.723	0.722	0.721	0.722	0.720	0.722	0.720
50	0.724	0.723	0.721	0.725	0.725	0.723	0.726	0.723	0.721	0.726	0.722	0.722	0.724	0.723	0.722	0.721	0.723	0.719	0.722	0.719
51	0.725	0.724	0.723	0.726	0.726	0.723	0.725	0.724	0.721	0.726	0.723	0.722	0.725	0.723	0.723	0.721	0.725	0.719	0.721	0.720
52	0.725	0.725	0.722	0.728	0.726	0.724	0.727	0.724	0.722	0.728	0.723	0.722	0.726	0.725	0.724	0.722	0.724	0.720	0.722	0.719
53	0.724	0.725	0.722	0.726	0.726	0.723	0.727	0.725	0.722	0.726	0.722	0.722	0.725	0.725	0.723	0.723	0.725	0.720	0.722	0.720
54	0.725	0.726	0.722	0.727	0.726	0.724	0.727	0.725	0.723	0.727	0.723	0.723	0.725	0.726	0.724	0.723	0.725	0.721	0.723	0.720
55	0.725	0.725	0.722	0.727	0.726	0.724	0.728	0.724	0.724	0.727	0.725	0.723	0.726	0.727	0.725	0.723	0.725	0.721	0.722	0.720
56	0.726	0.726	0.722	0.727	0.725	0.723	0.727	0.725	0.723	0.727	0.724	0.724	0.724	0.725	0.725	0.724	0.725	0.721	0.722	0.720
57	0.724	0.726	0.723	0.726	0.725	0.724	0.727	0.725	0.724	0.727	0.726	0.724	0.725	0.728	0.725	0.724	0.725	0.720	0.722	0.719
58	0.725	0.726	0.724	0.728	0.725	0.723	0.728	0.726	0.725	0.727	0.725	0.726	0.725	0.727	0.726	0.725	0.725	0.722	0.723	0.721
59	0.726	0.727	0.724	0.728	0.726	0.723	0.728	0.726	0.724	0.729	0.726	0.725	0.725	0.727	0.725	0.725	0.726	0.722	0.722	0.722
60	0.732	0.727	0.724	0.727	0.725	0.722	0.728	0.727	0.724	0.728	0.726	0.727	0.724	0.726	0.725	0.725	0.727	0.722	0.723	0.722
61	0.732	0.733	0.724	0.726	0.726	0.723	0.727	0.726	0.723	0.727	0.725	0.725	0.724	0.727	0.726	0.725	0.727	0.721	0.724	0.720
62	0.733	0.733	0.734	0.728	0.725	0.723	0.728	0.726	0.725	0.728	0.727	0.726	0.724	0.727	0.727	0.725	0.726	0.722	0.723	0.721
63	0.735	0.734	0.734	0.736	0.725	0.724	0.728	0.725	0.724	0.729	0.726	0.726	0.726	0.727	0.727	0.726	0.727	0.723	0.725	0.721
64	0.734	0.734	0.734	0.736	0.734	0.724	0.727	0.726	0.724	0.727	0.726	0.726	0.725	0.727	0.726	0.725	0.727	0.724	0.725	0.722
65	0.732	0.737	0.736	0.737	0.735	0.733	0.726	0.726	0.726	0.731	0.728	0.727	0.726	0.729	0.728	0.726	0.729	0.725	0.725	0.722
66	0.733	0.738	0.736	0.737	0.735	0.733	0.735	0.726	0.724	0.729	0.728	0.727	0.725	0.728	0.727	0.726	0.727	0.725	0.724	0.723
67	0.734	0.738	0.738	0.737	0.735	0.733	0.736	0.736	0.725	0.729	0.728	0.729	0.725	0.728	0.727	0.727	0.728	0.726	0.726	0.724
68	0.735	0.738	0.738	0.737	0.735	0.734	0.736	0.736	0.733	0.728	0.727	0.728	0.727	0.728	0.727	0.727	0.728	0.725	0.727	0.723
69	0.735	0.738	0.738	0.738	0.735	0.735	0.735	0.736	0.734	0.738	0.728	0.729	0.726	0.729	0.728	0.727	0.727	0.726	0.726	0.724
70	0.735	0.739	0.738	0.738	0.736	0.735	0.737	0.737	0.734	0.739	0.737	0.729	0.725	0.728	0.727	0.728	0.729	0.725	0.726	0.723
71	0.735	0.738	0.739	0.737	0.736	0.735	0.735	0.736	0.735	0.738	0.737	0.735	0.726	0.728	0.727	0.728	0.728	0.726	0.726	0.724
72	0.735	0.738	0.738	0.738	0.735	0.736	0.735	0.737	0.736	0.738	0.738	0.735	0.737	0.729	0.729	0.727	0.728	0.725	0.728	0.724
73	0.736	0.738	0.737	0.738	0.736	0.737	0.737	0.737	0.734	0.738	0.738	0.737	0.736	0.735	0.726	0.727	0.729	0.724	0.727	0.723
74	0.735	0.738	0.739	0.737	0.735	0.736	0.737	0.738	0.735	0.738	0.740	0.736	0.737	0.735	0.735	0.726	0.728	0.725	0.727	0.723
75	0.734	0.737	0.737	0.738	0.736	0.735	0.735	0.734	0.734	0.738	0.736	0.737	0.734	0.734	0.734	0.732	0.727	0.724	0.728	0.723
76	0.735	0.737	0.738	0.738	0.736	0.736	0.736	0.734	0.733	0.738	0.736	0.735	0.735	0.734	0.734	0.734	0.734	0.723	0.727	0.722
77	0.734	0.737	0.737	0.737	0.735	0.734	0.736	0.735	0.733	0.738	0.736	0.735	0.735	0.733	0.735	0.734	0.733	0.729	0.726	0.722
78	0.736	0.737	0.737	0.738	0.736	0.735	0.736	0.734	0.734	0.737	0.736	0.736	0.736	0.734	0.735	0.734	0.733	0.730	0.734	0.722
79	0.733	0.734	0.736	0.737	0.734	0.733	0.733	0.732	0.732	0.735	0.733	0.733	0.733	0.731	0.733	0.733	0.731	0.728	0.732	0.729
80	0.734	0.735	0.737	0.737	0.737	0.734	0.735	0.734	0.732	0.737	0.735	0.735	0.734	0.733	0.735	0.733	0.732	0.730	0.733	0.731
81	0.735	0.737	0.738	0.738	0.737	0.735	0.736	0.735	0.734	0.738	0.736	0.735	0.737	0.735	0.736	0.734	0.733	0.730	0.734	0.732
82	0.734	0.738	0.738	0.736	0.737	0.735	0.738	0.738	0.737	0.737	0.738	0.736	0.736	0.736	0.737	0.736	0.737	0.732	0.733	0.734
83	0.735	0.739	0.739	0.737	0.737	0.736	0.739	0.737	0.737	0.738	0.739	0.738	0.737	0.735	0.737	0.735	0.736	0.732	0.735	0.734
84	0.734	0.738	0.739	0.736	0.737	0.734	0.738	0.737	0.736	0.738	0.738	0.736	0.737	0.736	0.737	0.735	0.737	0.732	0.736	0.734
85	0.734	0.737	0.738	0.736	0.737	0.735	0.738	0.737	0.736	0.739	0.739	0.735	0.737	0.736	0.738	0.735	0.738	0.732	0.735	0.734
86	0.735	0.739	0.738	0.738	0.737	0.736	0.738	0.736	0.737	0.740	0.741	0.738	0.738	0.736	0.737	0.736	0.736	0.733	0.735	0.735
87	0.736	0.739	0.739	0.738	0.737	0.735	0.739	0.736	0.738	0.740	0.739	0.739	0.737	0.737	0.738	0.736	0.737	0.733	0.736	0.734
88	0.735	0.739	0.739	0.738	0.738	0.737	0.739	0.737	0.738	0.740	0.740	0.738	0.738	0.737	0.738	0.736	0.736	0.733	0.735	0.734
89	0.734	0.738	0.737	0.738	0.738	0.737	0.740	0.737	0.738	0.739	0.740	0.738	0.737	0.736	0.738	0.736	0.737	0.733	0.736	0.736
90	0.735	0.739	0.738	0.738	0.738	0.737	0.739	0.736	0.737	0.739	0.740	0.738	0.738	0.738	0.739	0.736	0.737	0.734	0.736	0.735
91	0.734	0.738	0.739	0.737	0.738	0.735	0.738	0.737	0.737	0.739	0.742	0.737	0.738	0.737	0.738	0.736	0.738	0.733	0.736	0.736
92	0.735	0.738	0.739	0.738	0.738	0.737	0.738	0.736	0.738	0.740	0.741	0.738	0.737	0.737	0.739	0.736	0.737	0.733	0.736	0.736
93	0.736	0.737	0.739	0.738	0.738	0.737	0.738	0.736	0.738	0.740	0.741	0.738	0.738	0.737	0.739	0.737	0.737	0.734	0.736	0.736
94	0.735	0.738	0.739	0.739	0.738	0.737	0.739	0.736	0.738	0.740	0.740	0.737	0.737	0.736	0.739	0.736	0.738	0.733	0.737	0.736
95	0.734	0.737	0.739	0.738	0.738	0.736	0.739	0.736	0.737	0.739	0.741	0.738	0.738	0.738	0.739	0.737	0.737	0.733	0.737	0.737
96	0.735	0.737	0.738	0.740	0.739	0.737	0.739	0.736	0.738	0.740	0.740	0.738	0.738	0.736	0.739	0.736	0.737	0.734	0.738	0.736
97	0.737	0.738	0.739	0.738	0.739	0.737	0.738	0.736	0.739	0.741	0.740	0.738	0.737	0.735	0.739	0.737	0.736	0.733	0.737	0.736
98	0.736	0.737	0.739	0.739	0.738	0.736	0.737	0.736	0.737	0.741	0.740	0.737	0.737	0.737	0.739	0.737	0.736	0.733	0.739	0.736

Max Train Bin	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99
0	0.562	0.558	0.559	0.560	0.560	0.560	0.559	0.556	0.560	0.559	0.562	0.559	0.560	0.556	0.563	0.560	0.557	0.553	0.568	0.562
1	0.593	0.592	0.594	0.593	0.592	0.592	0.593	0.594	0.590	0.591	0.591	0.593	0.594	0.592	0.592	0.586	0.588	0.587	0.580	0.597
2	0.605	0.605	0.604	0.602	0.602	0.602	0.602	0.603	0.601	0.602	0.603	0.603	0.601	0.606	0.601	0.600	0.597	0.602	0.598	0.583
3	0.619	0.612	0.619	0.617	0.615	0.614	0.617	0.615	0.615	0.617	0.617	0.617	0.616	0.615	0.616	0.614	0.612	0.611	0.610	0.642
4	0.628	0.627	0.624	0.624	0.622	0.627	0.621	0.626	0.627	0.620	0.625	0.625	0.626	0.623	0.623	0.624	0.618	0.623	0.619	0.618
5	0.631	0.638	0.635	0.635	0.633	0.634	0.634	0.636	0.637	0.631	0.634	0.635	0.637	0.632	0.634	0.633	0.630	0.628	0.628	0.632
6	0.640	0.636	0.641	0.638	0.637	0.638	0.638	0.641	0.641	0.637	0.639	0.641	0.642	0.636	0.637	0.638	0.636	0.636	0.623	0.665
7	0.646	0.646	0.643	0.646	0.643	0.641	0.642	0.643	0.643	0.641	0.643	0.643	0.645	0.643	0.640	0.644	0.635	0.638	0.641	0.668
8	0.653	0.648	0.651	0.650	0.649	0.648	0.648	0.650	0.651	0.645	0.650	0.651	0.653	0.645	0.648	0.648	0.644	0.641	0.640	0.652
9	0.662	0.657	0.656	0.657	0.654	0.654	0.654	0.656	0.656	0.654	0.654	0.658	0.659	0.654	0.654	0.654	0.651	0.647	0.653	0.669
10	0.661	0.658	0.660	0.660	0.657	0.659	0.657	0.660	0.659	0.657	0.658	0.660	0.661	0.653	0.656	0.656	0.653	0.649	0.650	0.646
11	0.662	0.660	0.660	0.663	0.662	0.661	0.659	0.663	0.659	0.661	0.661	0.662	0.664	0.656	0.661	0.657	0.656	0.653	0.650	0.641
12	0.667	0.665	0.665	0.665	0.667	0.665	0.665	0.666	0.667	0.666	0.665	0.665	0.666	0.661	0.663	0.662	0.659	0.656	0.652	0.661
13	0.671	0.670	0.670	0.670	0.671	0.668	0.667	0.668	0.668	0.668	0.668	0.669	0.668	0.664	0.665	0.664	0.661	0.662	0.665	0.668
14	0.674	0.673	0.671	0.672	0.674	0.670	0.669	0.673	0.671	0.672	0.669	0.673	0.671	0.671	0.671	0.669	0.666	0.664	0.678	0.655
15	0.679	0.679	0.675	0.678	0.678	0.674	0.674	0.675	0.676	0.675	0.676	0.676	0.677	0.672	0.676	0.673	0.670	0.668	0.668	0.686
16	0.680	0.680	0.677	0.678	0.678	0.679	0.677	0.676	0.678	0.677	0.677	0.677	0.678	0.677	0.677	0.675	0.673	0.671	0.683	0.697
17	0.682	0.684	0.682	0.681	0.682	0.677	0.678	0.679	0.682	0.679	0.680	0.682	0.681	0.680	0.678	0.679	0.676	0.674	0.681	0.692
18	0.687	0.688	0.684	0.683	0.683	0.682	0.682	0.684	0.682	0.683	0.682	0.684	0.682	0.680	0.681	0.680	0.677	0.677	0.678	0.676
19	0.690	0.689	0.687	0.685	0.686	0.683	0.684	0.682	0.685	0.684	0.683	0.686	0.684	0.682	0.682	0.683	0.677	0.675	0.670	0.687
20	0.690	0.690	0.688	0.687	0.686	0.684	0.687	0.684	0.686	0.685	0.685	0.687	0.686	0.683	0.683	0.684	0.679	0.679	0.682	0.697
21	0.691	0.691	0.689	0.689	0.689	0.687	0.687	0.687	0.686	0.689	0.687	0.688	0.687	0.686	0.684	0.687	0.680	0.681	0.675	0.703
22	0.692	0.693	0.689	0.689	0.689	0.689	0.688	0.688	0.689	0.690	0.686	0.688	0.686	0.687	0.686	0.687	0.682	0.684	0.687	0.696
23	0.694	0.694	0.693	0.691	0.692	0.690	0.690	0.690	0.689	0.691	0.689	0.690	0.690	0.690	0.688	0.688	0.684	0.686	0.676	0.682
24	0.693	0.693	0.692	0.692	0.690	0.691	0.690	0.691	0.690	0.690	0.689	0.691	0.689	0.688	0.688	0.689	0.686	0.686	0.684	0.704
25	0.697	0.697	0.695	0.694	0.694	0.691	0.694	0.693	0.693	0.694	0.691	0.694	0.693	0.691	0.691	0.691	0.687	0.688	0.685	0.700
26	0.702	0.701	0.700	0.699	0.697	0.696	0.697	0.695	0.696	0.696	0.695	0.697	0.696	0.696	0.695	0.694	0.692	0.689	0.687	0.690
27	0.699	0.701	0.698	0.697	0.700	0.696	0.697	0.696	0.696	0.697	0.697	0.697	0.698	0.697	0.695	0.696	0.692	0.689	0.688	0.703
28	0.702	0.699	0.700	0.699	0.700	0.697	0.697	0.699	0.697	0.699	0.697	0.698	0.699	0.696	0.695	0.696	0.692	0.690	0.691	0.697
29	0.694	0.694	0.694	0.693	0.693	0.694	0.690	0.693	0.692	0.692	0.693	0.694	0.691	0.691	0.692	0.690	0.689	0.688	0.687	0.692
30	0.697	0.696	0.694	0.694	0.695	0.696	0.693	0.694	0.693	0.694	0.693	0.694	0.692	0.691	0.693	0.692	0.690	0.688	0.684	0.701
31	0.697	0.698	0.696	0.696	0.697	0.695	0.695	0.696	0.695	0.694	0.694	0.696	0.694	0.694	0.694	0.693	0.692	0.691	0.687	0.690
32	0.710	0.711	0.708	0.708	0.708	0.706	0.706	0.704	0.704	0.704	0.706	0.707	0.706	0.705	0.703	0.703	0.698	0.699	0.702	0.708
33	0.712	0.710	0.708	0.711	0.708	0.709	0.707	0.706	0.706	0.706	0.706	0.707	0.706	0.708	0.704	0.704	0.700	0.698	0.705	0.713
34	0.714	0.714	0.710	0.712	0.709	0.710	0.708	0.707	0.708	0.708	0.709	0.707	0.708	0.709	0.707	0.706	0.701	0.703	0.696	0.714
35	0.714	0.712	0.711	0.714	0.710	0.710	0.710	0.708	0.709	0.708	0.709	0.710	0.711	0.711	0.707	0.707	0.702	0.701	0.704	0.713
36	0.712	0.713	0.711	0.710	0.710	0.711	0.710	0.709	0.710	0.707	0.709	0.707	0.710	0.709	0.707	0.704	0.703	0.703	0.705	0.727
37	0.715	0.714	0.713	0.715	0.711	0.712	0.709	0.709	0.710	0.709	0.710	0.710	0.712	0.711	0.709	0.709	0.703	0.705	0.705	0.718
38	0.713	0.712	0.709	0.712	0.711	0.710	0.710	0.708	0.707	0.708	0.708	0.708	0.709	0.709	0.708	0.706	0.703	0.705	0.701	0.715
39	0.715	0.713	0.712	0.713	0.711	0.711	0.711	0.709	0.709	0.708	0.709	0.710	0.713	0.711	0.709	0.709	0.703	0.707	0.700	0.715
40	0.715	0.712	0.711	0.713	0.711	0.711	0.710	0.709	0.711	0.709	0.710	0.710	0.711	0.710	0.709	0.708	0.702	0.706	0.709	0.711
41	0.716	0.715	0.715	0.716	0.713	0.713	0.713	0.711	0.712	0.711	0.711	0.712	0.714	0.713	0.711	0.709	0.703	0.707	0.705	0.715
42	0.715	0.714	0.712	0.715	0.712	0.713	0.713	0.710	0.711	0.710	0.712	0.711	0.713	0.712	0.711	0.710	0.704	0.709	0.707	0.717
43	0.718	0.716	0.714	0.717	0.714	0.714	0.713	0.712	0.713	0.713	0.713	0.714	0.715	0.714	0.713	0.711	0.706	0.711	0.703	0.723
44	0.717	0.715	0.717	0.718	0.713	0.715	0.713	0.713	0.713	0.712	0.715	0.713	0.714	0.714	0.712	0.711	0.706	0.710	0.704	0.715
45	0.718	0.716	0.716	0.719	0.713	0.716	0.715	0.714	0.714	0.713	0.714	0.714	0.716	0.714	0.713	0.712	0.707	0.711	0.707	0.715
46	0.719	0.719	0.716	0.719	0.717	0.716	0.716	0.716	0.717	0.715	0.715	0.715	0.717	0.715	0.713	0.714	0.709	0.711	0.711	0.724
47	0.720	0.720	0.718	0.721	0.717	0.717	0.715	0.717	0.717	0.716	0.717	0.717	0.719	0.717	0.715	0.715	0.711	0.713	0.707	0.724
48	0.722	0.720	0.721	0.721	0.718	0.718	0.717	0.718	0.719	0.717	0.717	0.717	0.719	0.718	0.716	0.718	0.711	0.713	0.710	0.732
49	0.722	0.722	0.720	0.722	0.718	0.718	0.719	0.719	0.719	0.719	0.719	0.719	0.721	0.719	0.717	0.719	0.713	0.714	0.711	0.734
50	0.723	0.721	0.721	0.723	0.717	0.718	0.718	0.718	0.719	0.717	0.720	0.719	0.720	0.719	0.717	0.718	0.713	0.715	0.715	0.728
51	0.723	0.723	0.722	0.723	0.717	0.718	0.720	0.719	0.720	0.718	0.720	0.719	0.720	0.720	0.718	0.718	0.713	0.717	0.720	0.739
52	0.725	0.723	0.721	0.723	0.718	0.719	0.720	0.720	0.721	0.720	0.721	0.720	0.721	0.721	0.718	0.718	0.714	0.714	0.716	0.732
53	0.724	0.722	0.721	0.723	0.718	0.719	0.720	0.721	0.721	0.720	0.721	0.719	0.721	0.721	0.718	0.719	0.715	0.715	0.714	0.734
54	0.724	0.723	0.723	0.723	0.719	0.720	0.720	0.722	0.721	0.721	0.723	0.721	0.723	0.722	0.719	0.719	0.716	0.717	0.715	0.745
55	0.723	0.723	0.723	0.723	0.719	0.719	0.721	0.723	0.722	0.722	0.723	0.722	0.723	0.723	0.720	0.721	0.717	0.718	0.717	0.738
56	0.723	0.724	0.723	0.724	0.719	0.720	0.721	0.722	0.721	0.722	0.722	0.721	0.723	0.722	0.721	0.720	0.716	0.719	0.716	0.732
57	0.723	0.724	0.724	0.723	0.719	0.720	0.721	0.722	0.721	0.722	0.723	0.723	0.724	0.723	0.720	0.721	0.718	0.719	0.712	0.739
58	0.723	0.724	0.724	0.724	0.719	0.721	0.721	0.723	0.722	0.722	0.724	0.723	0.726	0.724	0.721	0.720	0.718	0.719	0.715	0.737
59	0.724	0.724	0.723	0.725	0.720	0.721	0.722	0.724	0.724	0.723	0.725	0.723	0.725	0.723	0.722	0.723	0.719	0.720	0.718	0.738
60	0.724	0.724	0.725	0.725	0.720	0.722	0.721	0.724	0.723	0.723	0.725	0.723	0.725	0.724	0.722	0.722	0.719	0.719	0.717	0.738
61	0.724	0.724	0.724	0.724	0.720	0.721	0.722	0.723	0.723	0.721	0.723	0.724	0.724	0.723	0.722	0.721	0.716	0.720	0.720	0.728
62	0.725	0.726	0.725	0.725	0.721	0.721	0.722	0.724	0.722	0.724	0.724	0.724	0.725	0.724	0.723	0.722	0.719	0.722	0.718	0.730
63	0.725	0.725	0.726	0.726	0.721	0.721	0.723	0.725	0.723	0.724	0.725	0.725	0.726	0.725	0.723	0.723	0.719	0.721	0.723	0.734
64	0.725	0.726	0.726	0.725	0.722	0.721	0.723	0.725	0.724	0.723	0.725	0.725	0.725	0.724	0.723	0.723	0.719	0.722	0.722	0.738
65	0.724	0.726	0.727	0.726	0.723	0.723	0.723	0.727	0.723	0.726	0.727	0.727	0.729	0.727	0.724	0.725	0.723	0.724	0.722	0.749
66	0.725	0.726	0.727	0.726	0.723	0.724	0.723	0.727	0.723	0.726	0.727	0.726	0.727	0.727	0.725	0.725	0.722	0.724	0.716	0.745
67	0.725	0.726	0.726	0.726	0.725	0.726	0.726	0.728	0.724	0.726	0.727	0.727	0.728	0.728	0.725	0.726	0.723	0.724	0.717	0.749
68	0.725	0.727	0.728	0.727	0.725	0.724	0.724	0.727	0.723	0.726	0.728	0.727	0.728	0.728	0.725	0.726	0.723	0.724	0.714	0.751
69	0.725	0.727	0.727	0.727	0.725	0.724	0.726	0.727	0.723	0.725	0.728	0.727	0.728	0.728	0.725	0.727	0.725	0.726	0.715	0.752
70	0.726	0.726	0.727	0.726	0.724	0.725	0.726	0.728	0.723	0.725	0.730	0.727	0.729	0.729	0.725	0.727	0.723	0.725	0.719	0.751
71	0.728	0.727	0.728	0.727	0.724	0.723	0.725	0.728	0.724	0.725	0.730	0.727	0.729	0.730	0.726	0.726	0.724	0.724	0.714	0.756
72	0.728	0.726	0.728	0.726	0.724	0.725	0.727	0.727	0.723	0.725	0.729	0.727	0.729	0.728	0.726	0.728	0.725	0.727	0.718	0.755
73	0.729	0.727	0.728	0.727	0.725	0.724	0.726	0.727	0.724	0.725	0.729	0.727	0.730	0.729	0.726	0.727	0.726	0.727	0.718	0.755
74	0.728	0.726	0.730	0.728	0.724	0.725	0.726	0.727	0.724	0.725	0.730	0.727	0.729	0.729	0.727	0.727	0.726	0.727	0.718	0.751
75	0.728	0.726	0.727	0.726	0.723	0.724	0.726	0.726	0.724	0.723	0.729	0.727	0.729	0.728	0.725	0.727	0.723	0.726	0.719	0.741
76	0.728	0.727	0.726	0.727	0.724	0.725	0.725	0.726	0.723	0.724	0.730	0.727	0.730	0.727	0.726	0.727	0.723	0.726	0.717	0.741
77	0.728	0.726	0.727	0.728	0.723	0.724	0.724	0.727	0.724	0.723	0.729	0.727	0.730	0.727	0.725	0.727	0.724	0.725	0.716	0.739
78	0.727	0.727	0.728	0.727	0.722	0.724	0.725	0.726	0.724	0.723	0.729	0.728	0.729	0.728	0.725	0.727	0.723	0.727	0.717	0.739
79	0.725	0.725	0.726	0.727	0.723	0.723	0.724	0.725	0.723	0.723	0.728	0.725	0.728	0.726	0.725	0.726	0.723	0.724	0.716	0.744
80	0.733	0.725	0.727	0.727	0.723	0.723	0.725	0.727	0.724	0.723	0.730	0.727	0.730	0.728	0.726	0.727	0.725	0.727	0.718	0.738
81	0.735	0.733	0.728	0.726	0.723	0.724	0.724	0.727	0.724	0.723	0.731	0.727	0.730	0.729	0.728	0.728	0.725	0.726	0.716	0.742
82	0.737	0.734	0.735	0.726	0.726	0.726	0.726	0.729	0.727	0.726	0.732	0.727	0.732	0.732	0.729	0.730	0.730	0.729	0.722	0.763
83	0.737	0.733	0.735	0.735	0.726	0.726	0.726	0.728	0.728	0.728	0.733	0.728	0.732	0.731	0.731	0.730	0.730	0.730	0.720	0.759
84	0.738	0.735	0.736	0.736	0.736	0.726	0.726	0.728	0.728	0.727	0.732	0.729	0.731	0.731	0.729	0.730	0.731	0.731	0.716	0.766
85	0.737	0.736	0.737	0.736	0.736	0.734	0.726	0.729	0.728	0.727	0.732	0.728	0.731	0.730	0.730	0.730	0.731	0.731	0.719	0.763
86	0.738	0.735	0.736	0.736	0.735	0.734	0.733	0.727	0.726	0.726	0.732	0.729	0.732	0.730	0.731	0.730	0.730	0.732	0.719	0.762
87	0.738	0.734	0.737	0.736	0.735	0.734	0.733	0.735	0.726	0.726	0.732	0.729	0.732	0.730	0.731	0.731	0.730	0.731	0.722	0.768
88	0.739	0.736	0.737	0.737	0.736	0.736	0.734	0.736	0.734	0.726	0.732	0.729	0.732	0.731	0.731	0.731	0.731	0.732	0.723	0.755
89	0.738	0.735	0.737	0.737	0.736	0.736	0.735	0.735	0.734	0.735	0.731	0.728	0.732	0.731	0.731	0.731	0.731	0.733	0.722	0.759
90	0.739	0.737	0.737	0.737	0.736	0.736	0.735	0.736	0.735	0.736	0.740	0.729	0.731	0.731	0.730	0.732	0.731	0.733	0.724	0.746
91	0.740	0.737	0.738	0.738	0.736	0.737	0.736	0.736	0.736	0.736	0.741	0.738	0.731	0.731	0.731	0.731	0.731	0.734	0.724	0.744
92	0.740	0.738	0.738	0.738	0.736	0.736	0.736	0.736	0.735	0.736	0.740	0.739	0.738	0.731	0.731	0.732	0.731	0.734	0.726	0.749
93	0.740	0.738	0.738	0.738	0.737	0.738	0.737	0.736	0.736	0.737	0.742	0.739	0.740	0.738	0.731	0.732	0.731	0.734	0.723	0.756
94	0.740	0.738	0.738	0.738	0.737	0.738	0.736	0.737	0.735	0.735	0.741	0.739	0.739	0.738	0.738	0.731	0.731	0.734	0.724	0.758
95	0.741	0.739	0.738	0.740	0.737	0.738	0.738	0.736	0.737	0.737	0.743	0.740	0.740	0.739	0.739	0.738	0.732	0.735	0.723	0.765
96	0.740	0.737	0.738	0.737	0.736	0.738	0.736	0.736	0.736	0.736	0.741	0.739	0.738	0.738	0.738	0.736	0.738	0.733	0.722	0.748
97	0.740	0.737	0.739	0.738	0.737	0.738	0.736	0.737	0.736	0.736	0.741	0.739	0.738	0.737	0.738	0.736	0.737	0.740	0.719	0.748
98	0.739	0.738	0.739	0.737	0.736	0.737	0.737	0.737	0.736	0.736	0.741	0.738	0.738	0.737	0.739	0.736	0.737	0.738	0.737	0.745

Table 4: ProNE Cumulative Forecasting Results