Studying the Evolution of Scientific Topics and their Relationships

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Abstract

We propose a study of the development of scientific topics through time, as well as the relations between them within the scientific field of computational linguistics and across subfields. We use topic modeling to analyze scientific texts published in the ACL Anthology, and introduce a categorization of topics in our field into 3 types: tasks, algorithms, and data. In order to understand how topics emerge, evolve, and gradually disappear over time, we analyze the evolution of these topics across time through several case studies. We further include in our analysis papers published in NeurIPS, and try to understand whether there was any influence between topics in this conference focused on neural methods and computational linguistics conferences, as well as measure the divergence over time between conferences in terms of the topics approached. We additionally look at the relationships between topics, categorizing them into types of competing or cooperating topics.

1 Introduction

Scientific fields progress through innovation. Science functions under the premise that, when new better topics appear in research, they overtake the old ones and contribute to shaping the progress of the research field (Kuhn, 2012). Nevertheless, scientific topics evolve interdependently (the appearance and popularity of one topic may affect the popularity of another) and oftentimes, the focus of research in a certain field is also influenced by topics in other related subfields.

We propose a multidimensional approach for studying scientific topics and their evolution, by analyzing our field of research - computational linguistics - from several points of view: we look at the parallel evolution of topics in computational linguistics and their popularity over time, as well as how they relate to each other, engaging in cooperating or competing relationships. We also extend this perspective by considering the interplay of topics within a field, as well as the context in which they appear, and how the same topic is portrayed in different subfields, with a focus on the mutual influence between ideas in computational linguistics and those in the related field of neural networks.

Among studies that track the evolution of topics in scientific texts, Hall et al. (2008) focused on scientific text in computational linguistics, analyzing papers published in ACL, EMNLP and COLING between 1978 and 2006. The authors identify increasing and decreasing trends up to 2006, and make predictions about the subsequent evolution of the field. We continue the analysis including articles published up until the end of 2018, and uncover current shifts and trends that may not have been predictable 15 years ago - such as the rise of neural networks methods.

In our work, we study topics across three types: tasks, algorithms and data. Moreover, our aim is to further and complement the previous explorations of topics in computational linguistics not only by extending the analysis to recent years, but also by looking at relations between topics within and across fields. We analyze texts in four top computational linguistics conferences (adding NAACL to the three conferences analyzed in (Hall et al., 2008)). We additionally propose an exploration of topics across conferences and subfields, and include in our analysis papers published in the Conference on Neural Information Processing Systems (NeurIPS), which is a machine learning conference focused on neural networks. Considering that in recent years neural networks have almost dominated methods used in computational linguistics, we try to understand how topics approached in computational linguistics relate to those in the more focused field of neural networks, and whether and how they

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migrate between these conferences.

Our analysis of topic relationships within computational linguistics is inspired from Tan et al. (2017), in which the authors propose a way to classify topic relationships into four types, based on their co-occurrence in text and the degree of correlation between their popularity over time. In our paper, we extend this and take a deeper look at the relations existing between topics in scientific text. We propose interpretations of topic relationships in the context of a scientific domain, and report interesting findings on how these types of relationships manifest between scientific topics, discovering, for example, which algorithms in computational linguistics are compatible with certain tasks (such as neural machine translation and RNNs), or finding pairs of topics that represent algorithms which have replaced one another along the history of computational linguistics (such as statistical machine translation and neural machine translation).

2 Previous work

Multiple previous studies have looked at evolution of topics through time, analyzing texts of various genres, from news (Michel et al., 2011; Rule et al., 2015) to emails (Wang and McCallum, 2006) to scientific articles (Hall et al., 2008; Prabhakaran et al., 2016; Griffiths and Steyvers, 2004; Blei and Lafferty, 2006; Anderson et al., 2012).

Popular choices for representing topics include topic models, to which some studies add variations specific to tracking trends over time, such as the continuous-time model proposed by Wang and McCallum (2006), the generative model proposed by Bolelli et al. (2009a,b), or the dynamic topic model (Blei and Lafferty, 2006). Hall et al. (2008) use an approach based on topic modeling, and focus on scientific texts in computational linguistics, analyzing papers published in ACL, EMNLP and COLING between 1978 and 2006. Gollapalli and Li (2015) use topic models and keyphrase extraction to compare topics in ACL and EMNLP. In other studies on scientific articles, topic representations are enriched with additional features such as citations (He et al., 2009). Citations and citation networks have been leveraged extensively in previous studies for tracking scientific topics (Shibata et al., 2008, 2009; Jurgens et al., 2018), analyzing the structure of the scientific community (Leicht et al., 2007), or summarizing scientific papers (Qazvinian and Radev, 2008), or entire technical topics (Qazvinian et al., 2013). Other authors make use of rhetorical framing to predict the patterns present in the development of scientific topics (Prabhakaran et al., 2016).

Not as many studies attempt to provide in-depth systematic analyses of the relations between topics within a field or across fields, independently from the publications where they occur. Zhang et al. (2017) introduce a learning technique to identify the evolutionary relationships (e.g., topic evolution, fusion, death, and novelty) between scientific topics. Grudin (2009) study the particular relationship between the field of AI and Human Computer Interaction. Shi et al. (2010) propose a temporal comparison of grant proposals and academic publications, in an attempt to understand which precedes the other and how they influence each other. In one of the most extensive studies on the topic (Tan et al., 2017), the authors propose a systematic way of classifying relations between topics into four types of cooperating or competing topics, based on their patterns of co-occurrence and prevalence correlation: friendships, arms-race, head-to-head, and tryst. We build on this framework in our analysis of the field in the following sections.

3 Dataset

Our study focuses on topics in computational linguistics and their evolution. For exploring this topic, we make use of articles published in the ACL Anthology (Bird et al., 2008; Radev et al., 2013) from its inception. We collect all papers published in four top conferences: ACL, EMNLP, COLING and NAACL over time, obtaining a total of 14,737 computational linguistics articles overall. We will further refer to the set of computational linguistics conferences we considered by using the general term *ACL+*.

For the second stage of our study, we additionally use articles published in the NeurIPS conference, from which we collect all articles published since 1994, in total 6,520 articles. Table 1 shows the number of articles for each time period (across 5-year time spans) for the ACL+ conferences and NeurIPS. In Figure 1 we show the number of papers published as a time series, computed separately for each of the conferences considered. We make our collected dataset as well as code used for our experiments publicly available.[1]

[1] https://github.com/ananana/scientific_topics_history

Period	Number of articles	
	ACL+	NeurIPS
pre-1980	374	-
1980-1985	332	-
1986-1990	729	-
1991-1995	609	157
1996-2000	1108	842
2001-2005	950	767
2006-2010	3456	1449
2011-2015	3432	1091
2016-2018	3747	2214

Table 1: Number of articles per time period.

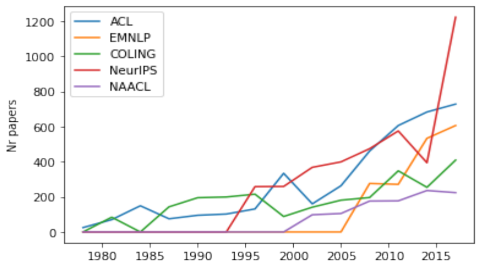


Figure 1: Number of published papers per conference.

4 Representation of ideas

We base our study on the premise proposed by Kuhn (2012) that science proceeds by shifting from one paradigm to another, viewing the evolution of science as a series of topics that follow and replace one another. Furthermore, we assume that these shifts in topics are directly reflected in shifts at the level of the vocabulary employed in the articles that discuss them.

Based on this assumption, we choose to represent topics by relying on topics extracted using unsupervised topic modeling, which treats documents as bags of words generated by one or more topics. We choose to measure the topics' evolution over time post-hoc, using a classical topic model and monitoring the change in topic prevalence over time. While dynamic topic models (Blei and Lafferty, 2006) allow to include temporal information in the generated labels themselves, they impose additional constraints on the time periods (for example assuming the changes between consecutive years are the same). We design our representation of topics starting from the observation that computational linguistics research can generally be described as comprising of a set of research tasks, which researchers aim to solve by employing appropriate algorithms, usually assisted by the use of datasets. Based on this assumption, we propose that topics in computational linguistics can naturally be categorized into 3 types: *tasks*, *algorithms* and *data*. As such, we propose a notion of *scientific topic* in our field which consists of both a topic and its category or type; in this view, a topic in computational linguistics can be defined as:

$$(\mathbf{topic}_t, \mathbf{type}_c),$$
$$type_c \in \{task, algorithm, data\}, topic_t \in T,$$

with T representing the list of topics generated by the Latent Dirichlet Allocation model (LDA) (Blei et al., 2003). These topic categories can be useful beyond our field and application, for example in question answering systems or paper recommendation systems (Augenstein et al., 2017; Park and Caragea, 2020; Luan et al., 2018; QasemiZadeh and Schumann, 2016). In order to identify the topics occurring in our corpus of scientific texts, we first train an LDA model on the full texts extracted from computational linguistics articles, and use it to extract a set of 100 topics which we will use to analyze the evolution of the field in the next stages of our study. We use the Mallet implementation of LDA[2], with parameters set to 100 topics, and 100 training passes. The asymmetric prior distribution was learned directly from the data. The resulted model has a topic coherence score of 0.484 according to the C_V coherence measure.

In order to maximize the quality of the produced topics, we first label the obtained sequences with POS tags and select only words with POS tags corresponding to content words: nouns, verbs, adjectives, and adverbs, and discard the rest. We lowercase and lemmatize the texts, and we extract bigrams and trigrams using PMI scores to select words which occur together with high probability and add them to our vocabulary and document representations. On the collection of articles published in the ACL Anthology preprocessed as described above, we train the topic model to extract 100 topics. We do not intervene with significant changes on the output of the model, and only add minor corrections, through manual curation: we remove 10 of the extracted topics which we do not consider to represent coherent or interesting ideas, and merge a few topics which were redundant. We are left with a total of 82 topics.

We then manually label each topic with one of the three proposed categories: *task* / *algorithm* / *data*, and obtain the final list of topics occurring in our corpus. Each topic can be assigned one or more types: we obtain 53 topics labelled as *tasks*, 33 of the topics are *algorithms*, while 7 topics fall

[2]http://mallet.cs.umass.edu/

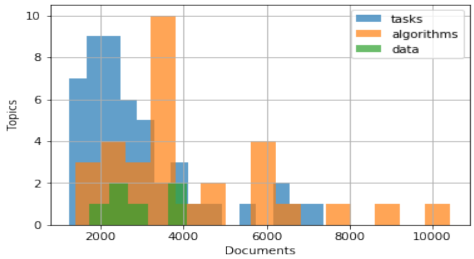


Figure 2: Distribution of topics for each type.

Topic	Top cited authors
Sentiment analysis (task)	J Wiebe, C Manning, L Lee, B Liu, B Pang
Topic models (algorithm)	C Manning, D Blei, A Mccallum, A Ng, Y Bengio
Coref. resolution (task)	C Manning, V Ng, D Klein, D Roth, C Cardie
Discourse (task)	D Marcu, A Joshi, C Manning, B Webber, B Grosz
Speech recognition (task)	E Shriberg, A Stolcke,H Ney, J Hirschberg, M Johnson
Neural MT (task, algorithm)	Y Bengio, K Cho, C Manning, I Sutskever, O Vinyals

Table 2: Most influential authors for a subset of topics.

into the *data* category. Some topics belonging to the *task* type are, for example, *morphology*, *event extraction*, or *summarization*. Topics such as *recurrent neural networks* or *topic models* fall under the category of *algorithms*, whereas *lexicons* and *parallel corpora* are categorized as *data* (or resources). A few topics refer to inherently connected tasks and algorithms, we label those with both types - as is the case of *neural machine translation* or *statistical machine translation*. The appendix lists the entire set of extracted topics, along with the top 10 keywords that are relevant for each, as well as their types. When topics were merged, the list of keywords relevant for each topic were merged into one larger list.

After having generated our list of topics, we further extract for each paper a list of relevant topics, considering only those which are present in the topic distribution for that document with a probability greater than 0.01. After this step, we are left with almost 13 relevant topics per article, on average. Finally, we measure the prevalence of a topic during a certain year by computing the empirical probability of its occurrence relative to the total number of topics that were approached overall in that year:

$$
\begin{aligned}
P(t|y) &= \sum_{d:t_d=y} P(t|d)P(d|y) \\
&= \frac{1}{C_y} \sum_{d:t_d=y} P(t|d) \\
&= \frac{1}{C_y} \sum_{d:t_d=y} \sum_{t_i^{'}\in d} I(t_i^{'} = t),
\end{aligned}
$$

where I is the indicator function, t_d is the year in which document d was published. The conditional probability of a topic given a document $P(t|d)$ is thus equal to 1 if the topic is present in the document and 0 otherwise. C_y represents the total number of documents written in a year y.

Figure 2 illustrates the distribution of topics across the computational linguistics corpus for each of the 3 topic types. Although the list of topics is generated using the full dataset of papers published, in our time series showing the popularity of topics in scientific papers over time we only consider papers published after 1978, when ACL was first organized. Similarly, when considering topics occurring in NeurIPS, our analyses will include the years when NeurIPS papers were published. All of the plots in the following sections show smoothed versions of the raw values of topic probabilities per year, using a rolling average with a window of two years.

5 Selected topics and trends

In order to narrow our focus to subsets of topics worthy of interesting insights, we propose a few ways to select topics that stand out and comment on their development over time - several case studies will be presented in the following subsections.

We also look into the most influential authors for each topic. We consider citations as an indicator of the influence of an author over a topic, and we thus measure the influence of each author for a topic by counting all of the occurrences of citations referring to the given author (regardless of the topic of the cited article) in all documents in our collection where the topic is present. Table 2 shows the top 5 most influential authors, ranked by number of citations, for a selection of topics.

Confirming and refuting predictions We first confront our findings with the predictions made in previous studies which looked at the evolution of scientific ideas in computational linguistics. Hall et al. (2008) identify a list of topics which were then on an increasing trend in 2006: *classification*, *probabilistic models*, *statistical parsing*, *statistical machine translation* and *lexical semantics*. We find among our topics those which best match their list, then analyze their evolution in order to see whether the predictions made then still hold today. Figure 3 shows the evolution of four of these topics

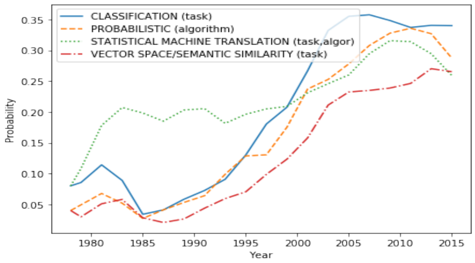


Figure 3: Topics on an increasing trend in 2006.

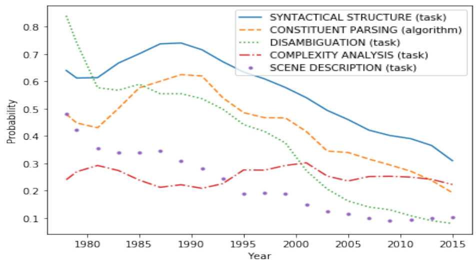


Figure 4: Top prevalent ideas in computational linguistics and their evolution.

until 2018: not all of the topics have maintained the same upward trend all through 2018. *Statistical machine translation* and *probabilistic models* suffer a decrease in popularity after 2010; *classification*, though still very popular, has reached a plateau, while *lexical semantics* seems to be still on an increasing trend, though less abruptly.

Most prevalent topics In our second case study we focus on the most prevalent topics overall, which we consider to be ones that over time have received the greatest attention in computational linguistics research. To find these, we average the probability of occurrence of a topic in each year, obtaining for each topic an overall score of prevalence:

$$\text{Prev}(t) = \frac{1}{|Y|}\sum_{y \in Y} P(t|y)$$

Figure 4 shows the evolution of the top 5 most prevalent topics in ACL+ across time. Most of these were very popular in the earlier days of computational linguistics and started to decrease around 1990, such as the topics related to syntax. *Complexity analysis* has a steady evolution across time, maintaining a relatively flat trend.

Topics with largest variation In our next analysis, we extract topics which vary most in popularity over time, hoping to discover topics which stand out because of their dramatic evolution over time. We do this by considering the distribution of probabilities for a topic over the years, and measuring its standard deviation, for each topic, then select those

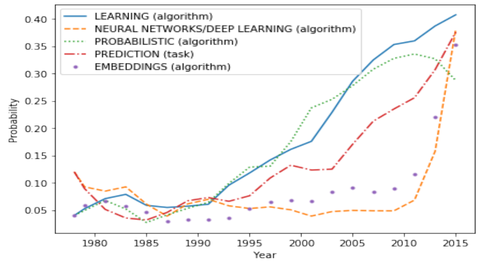


Figure 5: Topics which show greatest variation in linguistics conferences and their evolution.

topics where standard deviation is highest. The top 5 such topics and their evolution are illustrated in Figure 5. It seems that the most dramatic variations are related to recent increases in popularity of certain topics, most of which relate to machine learning. The steep and constant increase in popularity of the *learning* topic is apparent. Among the first 5 topics which vary most dramatically in popularity over time we find topics related to neural networks, which although very recent relative to the entire history of computational linguistics, have quickly caught up in popularity and even surpassed more traditional topics in the field, and show an abrupt increase in popularity after 2010. We analyze topics related to neural networks in more detail in the following paragraphs.

Neural networks In our final case study, we zoom in specifically on topics related to neural methods. These are shown in our previous results to be the stars of recent years in computational linguistics, showing an abrupt increase in popularity.

The list of topics generated by our LDA model produce no less than four distinct topics related directly to neural networks, found in computational linguistics papers, which is already remarkable for such a recent topic. These are: *neural networks*, *recurrent neural networks*, *neural machine translation* and *embeddings*. To these we add for our analysis the topic of *learning*, as the general class of topics under which neural networks fall, and whose evolution we also expect to be affected by the popularity of neural networks.

Furthermore, we compare the trends of neural network related topics in ACL+ to the same trends present in a conference focused primarily on neural networks: NeurIPS. In order to achieve this, we use our LDA model trained on ACL+ papers to extract topics from NeurIPS papers. Figure 6 shows the evolution of topics related to neural methods in papers published in ACL+ and in NeurIPS, respectively. Both papers in ACL+ and in NeurIPS

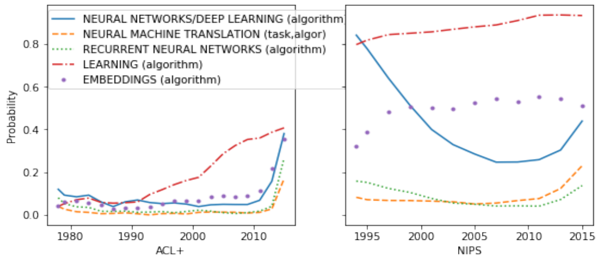


Figure 6: Neural topics evolution in ACL+ vs NeurIPS.

show the same steep increase in *recurrent neural networks* and *neural machine translation* starting between 2010 and 2015. *Learning* has a clearly more stable evolution in NeurIPS, where it has been a very popular topic from the beginning, as compared to computational linguistics, where it sees a steady and still continuing increase. Interestingly, *neural networks* as a general topic evolve differently in NeurIPS and ACL+: while in computational linguistics they are a recent topic, with a sudden increase in popularity after 2010, in NeurIPS they were widely discussed from 1994, and have suffered a decline up to 2010 when they started following the same upward trend.

6 Relationships between Topics

Methodology We use measures of relatedness between topics on two dimensions: co-occurrence and prevalence correlation, to characterize relationships into four major types of relations, which will be described and interpreted in more detail in this section: friendship, head-to-head, arms-race and tryst.

For categorizing pairs of topics into these types of relationships, we obtain co-occurrence scores for a pair of topics by computing the PMI score for the topics as they co-occur in documents, and compute the correlation score as the Pearson correlation between the time series represented by the topic's probability over time.

$$\text{Corr}(t_1, t_2) = \frac{\sum_y (P(t_1|y) - \overline{P(t_1|y)})((P(t_2|y) - \overline{P(t_2|y)})}{\sqrt{\sum_y (P(t_1|y) - \overline{P(t_1|y)})^2}\sqrt{\sum_y (P(t_2|y) - \overline{P(t_2|y)})^2}}$$

We then split each of these two dimensions into two classes (positive/negative co-occurrence, and positive/negative correlation), obtaining the four types of relationships from their combinations. We first standardize the distributions of co-occurrence and correlation scores, then split the relations landscape into four parts, depending on where they

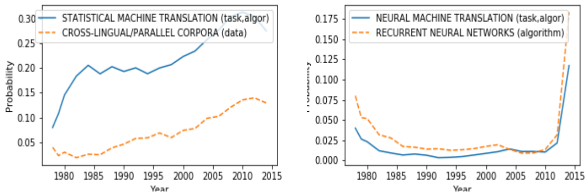


Figure 7: Examples of topics in friendship relationships and their evolution over time.

are situated on the two axes: positive/negative co-occurrence and positive/negative correlation.

We also compute a measure of strength of each relationship between a pair of topics, which is simply the product of the two scores, in absolute value. Sorted by the average strength of top 25 relations of that type, the relations rank as follows: friendships>head-to-head>tryst>arms-race. Table 3 shows the top pairs of topics with the strongest relations for each relation type, as well as their strength. The appendix contains tables with the top 10 relations for each relation and topic type.

We separately identify relations between different types of topics, and propose that some relations are more meaningful for certain topic pairings than others, depending on their types. For friendships, which refer to cooperating topics, we focus on topic pairs of different types, between which this relation is established, in order to discover the tasks go together with specific algorithms or datasets. For the other relation types (arms-race, head-to-head and tryst), we suggest that the cross-type topic pairs are less meaningful - since these types of relations can be interpreted as occurring between competing topics - for these we focus instead on same-type topic pairs (between tasks and tasks, algorithms and algorithms, data and data). In the tables presenting top relationships for each type, we restrict our focus to only topic pairs of types which can be meaningfully matched for each relation.

Friendships Two topics are "friends" if they tend to co-occur in the same texts and are also correlated in their prevalence over time. These are topics which go together, or "cooperate" - they are often found in the same documents and are used together in the analysis of a certain idea or area of interest. Figure 7 shows the top strongest friendship relationships between a task and an algorithm, and an algorithm and data, respectively. We discover, for example, that the *neural machine translation* task is most associated with the *recurrent neural networks* algorithm, and that for the task of *statistical machine translation*, *parallel corpora* are the most

Topic1	Topic2	Rel Type	Rel Strength
Neural MT (Task)	RNNs (Algorithm)	Friendship	13.03
Statistical MT (Task)	Parallel Corpora (Data)	Friendship	4.25
Transfer Learning (Algorithm)	Parallel Corpora (Data)	Friendship	3.76
Phonology (Task)	Semantic Role Labelling (Task)	Arms-race	1.98
Topic Models (Algorithm)	Dependency Parsing (Algorithm)	Arms-race	1.45
Unification (Task)	Neural MT (Task)	Head-to-head	6.27
Grammars (Algorithm)	Neural MT (Algorithm)	Head-to-head	5.40
Statistical MT (Algorithm)	Neural MT (Algorithm)	Tryst	2.91
Vision/Multimodal (Task)	Scene Description (Task)	Tryst	2.20
Dictionaries (Data)	Parallel Corpora (Data)	Tryst	2.23

Table 3: Top strongest relationships for each type, along with strength scores.

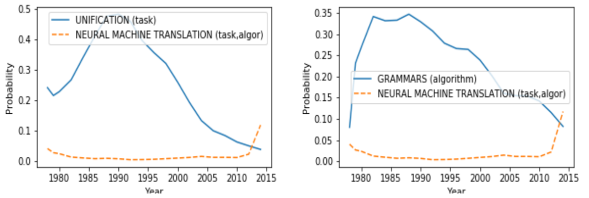


Figure 8: Examples of topics in head-to-head relationships and their evolution over time.

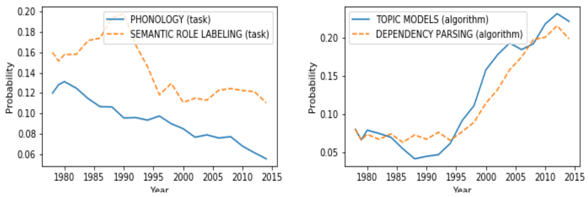


Figure 9: Examples of topics in arms race relationships and their evolution over time.

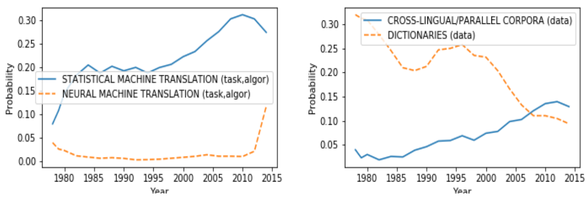


Figure 10: Examples of topics in tryst relationships and their evolution over time.

useful types of datasets.

Head to head Topics in a head-to-head relationship do not tend to co-occur in the same documents, and are anti-correlated over time. These are topics which have nothing in common, or are even rivals. In Figure 8 we can see the strongest head-to-head relationships in our corpus between tasks and algorithms respectively. One example is the relation between *grammars* and *neural machine translation*: these are rarely treated together in studies; more than that, while *neural machine translation* shows a recent increase in popularity, *grammars* are on a declining trend.

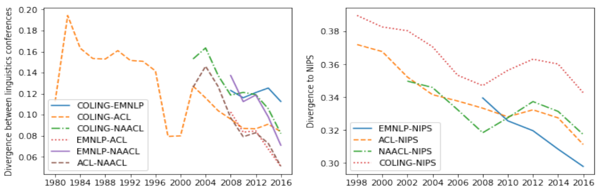
Arms race An arms-race relation characterizes topics that are correlated in their usage over time, but do not tend to co-occur within the same documents. Topics in this type of relationship tend to evolve in a similar pattern over time, possibly with an underlying common cause, even though they are not directly related: such is the case of many algorithms which were widely used before being recently replaced by neural networks. Figure 9 shows two such pairs of topics: *phonology* with *semantic role labelling*, and *topic models* with *dependency parsing*, which show similar decreasing trends, but are not referred to in the same articles.

Trysts Tryst is a relationship between topics which tend to co-occur in the same texts, but are anti-correlated in prevalence over time. We show that according to our study, this is one of the most interesting relations occurring between scientific topics, and propose that it is useful for discovering topics that are replaced by others: topics which share a common niche of the research field, but as one topic increases, the other decreases.

In Figure 10 we see two such relationships, which uncover interesting topic pairs. One is *statistical machine translation* versus *neural machine translation*, which is clearly a topic in the subfield of machine translation which has recently replaced the previous one as the primary focus of researchers. A similar phenomenon may have occurred for *data*-typed topics related to language resources: while *dictionaries* are overall more studied, they are on a decreasing trend, and have now been surpassed in popularity by *parallel corpora*.

7 Relations between conferences

Conference divergence In this part of our study we focus on the relations between conferences in computational linguistics. We compute divergence between conferences using Jensen-Shannon divergence applied on their topic distributions generated by papers published in each conference. Jensen-Shannon divergence is computed as the average of



(a) ACL+ conferences. (b) ACL+ vs NeurIPS.

Figure 11: Conference divergence over time for (a) ACL+ conferences and (b) ACL+ vs NeurIPS.

the KL divergences between each of the distributions and the average of the distributions. Its value is 0 for identical distributions, and tends to infinity as the two differ more and more.

Figure 11 shows the pairwise divergence over time between the computational linguistics conferences, as well as between the linguistics conferences and NeurIPS. The span of each pairwise divergence plot is limited to the span of the youngest conference in the pair; the values are smoothed using a rolling average with a window of 2 years. The plot reveals a decreasing trend for all conference pairs. ACL and COLING are the conferences with the oldest history, and show a steady but mild decrease in divergence throughout their evolution. The most similar conferences are shown to be ACL with EMNLP and with NAACL, which also show the steepest decrease in divergence.

We further extend our study to contrast the computational linguistics conferences with NeurIPS. It is interesting to see that, even though computational linguistics and neural methods are technically distinct fields, the linguistics conferences still tend to converge with NeurIPS over time (although the absolute divergence between these is still considerably higher than among computational linguistics conferences). The most similar conference to NeurIPS in terms of the topics approached seems to be EMNLP, which from its beginning was the closest to NeurIPS among all linguistics conferences. This is perhaps explained by the more applied character of EMNLP compared to the others. In contrast, COLING, the oldest and most linguistics-focused of the conferences, is the least similar to NeurIPS, although still shows a tendency towards decreasing this gap.

Synchronicity of topics across conferences Next, we introduce a second measure of similarity between conferences, this time over particular topics, in order to understand if conferences are synchronized in the topics they approach, and if this depends on particular sets of topics. Similarly to the measure of correlation used in the topic relationship analysis, the correlation between conferences for a subset of topics T is simply computed as the prevalence correlation of topics over time, on average, for each topic in the subset considered - this time between its evolution in the two conferences (or sets of conferences) to be analyzed.

Topic	Correlation
Reinforcement learning	0.93
Finite state machines	0.90
Disambiguation	0.90
Ranking	0.89
Neural machine translation	0.88

Table 4: Correlated topics between ACL+ and NeurIPS.

$$\mathrm{Corr}_T(c_1, c_2) = \frac{1}{|T|} \sum_{t \in T} \mathrm{Corr}_t(c_1, c_2),$$

where the correlation between two conferences for a certain topic t is defined as:

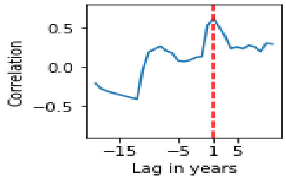
$$\frac{\sum_y (P(t|y,c_1) - \overline{P(t|y,c_1)})((P(t|y,c_2) - \overline{P(t|y,c_2)}))}{\sqrt{\sum_y (P(t|y,c_1) - \overline{P(t|y,c_1)})^2}\sqrt{\sum_y (P(t|y,c_2) - \overline{P(t|y,c_2)})^2}}$$

Using this measure we try to analyze how similar topics appear in different conferences over time, whether they follow similar trends or even influence each other.

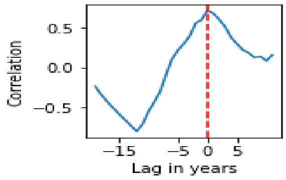
With an average correlation across all topics between NeurIPS and ACL+ of 0.71, this measure also shows a fairly similar evolution of topics between the conferences overall. We should note however that the topics used in the analysis were generated only from ACL+ papers, so topics exclusive to NeurIPS are not considered. We then rank the topics in our list by the correlation of their evolution in NeurIPS versus ACL+: 5 topics among the top 10 with the most correlated evolution are shown in Table 4.

Neural topics in computational linguistics versus NeurIPS Neural networks are an interesting subset of topics, which have very quickly become very popular in computational linguistics, and are today common as central foci of both ACL+ and NeurIPS. The average correlation between ACL Anthology and NeurIPS for topics related to neural methods (*neural networks*, *RNNs*, *neural MT* and *embeddings*), is 0.58, which interestingly is lower than the overall correlation across all topics.

We try to understand whether these conferences are synchronized in the way they approach topics and hope to understand, by comparing their evolution, if they mutually influence each other, especially regarding topics which are relevant for



(a) Neural networks topics



(b) All topics

Figure 12: Correlation between topics in ACL+ vs. NeurIPS papers adjusted with lags.

both. In order to analyze this phenomenon, we compute the correlation between the evolution of topics, this time introducing an artificial lag for the papers in ACL Anthology. The correlation of topic time series is computed using an updated definition of topic probability:

$$P_l(t|y) = P(t|y+l)$$

where l is a lag factor. Figure 12 shows the correlation between the evolution of topics after applying lags ranging from -25 to 25 years, for the full set of topics, as well as for the subset of topics related to neural networks. If there is any asynchronicity in the way topics appear in the two fields, the lag corresponding to the best correlation should help us find the delay with which topics gain popularity in the two conferences comparatively.

In our case, the optimal lag value across all topics is found to be exactly 0, whereas for neural topics the optimal lag is 1 year, showing a slight delay in the approach of neural method related topics in ACL+. Overall, ACL Anthology and NeurIPS seem fairly synchronized when in comes to innovation in this area.

8 Conclusions

We presented in this article an analysis of the topics found in computational linguistics conferences. We enhanced topics with their types by categorizing topics into tasks, algorithms, and data; and showed how the field has evolved, uncovering general trends, as well as new unforeseen trends such as the abrupt rise of neural network methods. We also identified the most influential authors for each topic, which can provide interesting insights assuming most cited authors when discussing an idea carry a big share of the responsibility of introducing and promoting the idea. A more sophisticated method for identifying influential authors could include a normalization factor based on the number of citations.

We additionally included a study of relations between topics and between subfields, to gain insight into the interplay between topics within and across fields. Our analysis confirmed the strong cooperative relationship between certain tasks and algorithms, such as neural machine translation and recurrent neural networks, but also revealed some interesting less obvious ways in which some topics relate - automatically identifying topics which replace others in the preference of scientists in a subfield (such as the change in paradigm for machine translation). In a separate experiment, we zoom in on the topic of neural networks, and compare the evolution of this topic in computational linguistics conferences to its parallel development in a conference dedicated to neural networks: NeurIPS.

Through the various complementary analyses we performed, we try to contribute to answering the question of how scientific topics emerge and gain traction by considering internal as well as external factors, and the scientific context in which trends appear and evolve. In the future, we would like to explore predictive models of what research topics would gain popularity in upcoming years. It would also be interesting to explore the effect of extracting more fine-grained topics, which could help with identifying more subtle trends - at the technical level, this would involve controlling the level of noise when increasing the number of topics. We will also explore in more depth the properties of the emerging network of topic relations, and the types of topics involved. Exploring more complex topic structures could help model more sophisticated notions such as scientific paradigms.

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Ethical Statement

All our data are extracted from publicly available sources. There are no ethical issues concerning our work.

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A Full list of topics

Domain adaptation (task)	domain adaptation adapt cross data share weight distribution multi scenario
Automata (algorithm)	string transformation finite operation transducer stre match regular weight symbol
Morphology (task)	morphological arabic morpheme stem suffix morphology prefix root affix inflection
Multi-word expressions (task)	expression collocation literal metaphor idiom mwe multiword descriptor mwes compositional
Sentiment analysis (task)	sentiment negative positive opinion polarity lexicon subjective classification subjectivity neutral
Trees (algorithm)	tree node child root subtree parent forest leaf branch depth
Reinforcement learning (algorithm)	action agent dialog policy reward instruction environment goal human reinforcement
SVMs (algorithm)	kernel svm bag vector bow space reranke linear clue support
Linear programming (algorithm)	constraint solution variable solve inference constrain ilp hard linear soft
Argument mining (task)	claim essay argument stance email evidence support debate statement topic
Topic models (algorithm)	document topic lda collection distribution topical latent content coherence background
Clustering (algorithm)	cluster clustering group induce merge class partition gold induction centroid
Language acquisition (task)	student author learner simplification write native readability grade complex read
Generation (task)	generation generator content record surface realization choice plan selection component
Named entity recognition (task)	token joint ner span crf sequence labeling normalization pipeline crfs
Discourse segmentation (task)	segment segmentation boundary unit length break sequence segmenter segmented window
Events/temporal (task)	temporal anchor event tense expression interval causal date day reference
Phonology (task)	letter phoneme syllable pronunciation phonetic vowel phonological stress consonant sound
Stylistics (task)	emotion social gender age group emotional participant people relationship person
Unification (task)	grammar unification head formalism cat description hpsg sign definition constraint
Language models (task)	gram probability bigram lm perplexity trigram unigram estimate vocabulary smooth
Textual entailment (task)	entailment inference hypothesis game textual player rte premise entail team
Biomedical (task)	cue medical citation abstract patient scientific scope biomedical cite article
Anaphoral/coref. resolution (task)	pronoun mention antecedent coreference resolution coreference_resolution anaphor resolve anaphoric reference
Dependency parsing (algorithm)	dependency parser parse head treebank tree dependent projective arc accuracy
Database/resources (data)	template database logical hybrid variable city expression meaning sql equation
Social media/web data (data)	user response post comment message conversation thread interaction feedback reply
Summarization (task)	summary summarization document rouge compression content length extractive human duc
Spelling correction (task)	error edit correction spelling revision rate confusion preposition incorrect learner
Evaluation/annotation (task)	human metric paraphrase reference correlation quality automatic judgment judge rating annotation annotator annotate agreement annotated gold scheme guideline automatic manual
Semantic role labelling (task)	argument predicate role arg srl syntactic identification propbank labeling core
Discourse (task)	discourse relation coherence connective implicit unit explicit paragraph marker rhetorical
Syntactic structure (task)	noun adjective compound head modifier modifi nominal determiner proper adverb verb subject object class preposition verbal noun passive argument syntactic syntactic linguistic syntax grammatical construction structural lexical deep surface phenomenon
Lexical semantics (task)	similarity vector cosine distributional sim distance weight relatedness space lsa
Learning (algorithm)	weight log parameter objective loss update optimization linear optimize paramet
Probabilistic models/distributions (algorithm)	distribution probability sample variable latent prior parameter estimate inference generative
Statistical MT (task,algorithm)	alignment align link probability ibm aligned null correspondence aligner heuristic translation translate quality mt target statistical translator smt reference bilingual translation bleu reorder decode smt hypothesis side decoder target chinese
Transfer learning (algorithm)	target transfer projection mapping project side map direct ds auxiliary
Speech recognition (task)	speech recognition speaker asr speak utterance acoustic transcript transcription prosodic
POS tagging (task)	tag pos tagger chunk accuracy tagging speech unknown tagset sequence treebank wsj fragment accuracy bracket pcfg probability np penn_treebank head
Lexicons (data)	lexical lexicon item entry lex lexeme coverage associate derive substitution
Constituent parsing (algorithm)	clause constituent head relative coordination subject element position complement mark parse parser grammar chart parsing span tree syntactic stage
Multilinguality (task)	resource french spanish multilingual pivot german corpora italian dutch portuguese

Table 5: Extracted topics and relevant keywords

Unsupervised learning (algorithm)	learning sample supervise unsupervised selection unlabeled iteration active supervised unlabeled
Ranking (algorithm)	candidate rank selection ranking denote weight framework ranker probability combination
Embeddings (algorithm)	vector embedding matrix embed space dimension vec dimensional mikolov tensor
Plan-based dialogue (task,algorithm)	dialogue utterance act speaker plan turn goal belief conversation request
Question answering (task)	question answer passage question_answere match paragraph trec reason factoid relevant
Event extraction (task)	event trigger mention extraction document ace attack argument entity relevant
Grammars (algorithm)	grammar derivation symbol terminal production nonterminal free cfg adjoin string
Logical forms (algorithm)	formula logic interpretation logical scope operator theory proposition predicate expression
Knowledge base (data)	entity mention wikipedia link person kb article document page title
Information extraction (task)	pattern seed extraction acquire acquisition bootstrappe web relationship discover match
Applications (task)	user tool module interface component support file format display design
Disambiguation (task)	interpretation ambiguity ambiguous processing preference strategy disambiguation attachment mechanism heuristic
Graphs/AMR (algorithm)	graph edge node vertex graphs connect amr weight propagation link
Neural networks (algorithm)	network layer neural cnn architecture rnn vector deep hide embedding
Narratives (task)	story genre book expert worker movie narrative human collect crowdsource
Ontologies (algorithm)	concept attribute hierarchy ontology taxonomy conceptual hypernym relation hierarchical link
Prediction (task)	predict prediction accuracy regression predictor error linear predictive variable effect
Quantitative analysis (algorithm)	frequency count probability distribution estimate occurrence corpora association statistical log
Vision/multimodal (task)	image visual video caption multimodal modality fusion textual human modal
Parallel corpora (data)	parallel bilingual monolingual corpora cross_lingual keyphrase comparable translation resource extraction
Neural MT (task,algorithm)	decoder encoder nmt sequence neural attention bleu decode rnn vocabulary
Recurrent neural networks (algorithm)	lstm attention vector memory embed mechanism embedding weight layer encode
Complexity analysis (task)	cost memory speed index fast run bit store key efficient
Opinion mining (task)	review aspect product rating restaurant opinion customer rationale hotel service
Social media (data)	tweet twitter social_media user twitt message hashtag detection post microblog
Transliteration (task)	character chinese transliteration oov hindi unknown accuracy char urdu ctb
Dictionaries (data)	dictionary definition code entry link cod dictionarie analogy database bank
Relation extraction (task)	relation extraction triple relational tuple open express relationship distant_supervision rel
Historical linguistics (task)	change family lemma cognate russian czech linguistic historical distance swedish
Wordnet/disambiguation (task,algorithm)	sense wordnet sens disambiguation synset wsd gloss disambiguate resource ambiguous
Dependency parsing (algorithm)	search transition stack beam prune action shift greedy partial configuration
Information retrieval (algorithm)	query search web retrieval document page relevant retrieve relevance engine
Supertagging (algorithm)	category ccg np derivation supertag composition lexical ambiguity supertagger ccgbank
Asian languages (task)	japanese expression korean bunsetsu particle accuracy wo marker element noun
Classification (algorithm)	class classification classifier accuracy classify svm binary decision classifi combination
Sequence analysis (algorithm)	sequence local position global distance length chain sequential gap permutation
Frame semantics (algorithm)	frame slot schema filler framenet fill intent element role slu
Dynamic programming (algorithm)	path factor ij lattice tuple cache length denote space dynamic
News articles (data)	article news company year political country day people issue market
Scene description (task)	object description property expression $\mu i\_\mu i$ reference scene referent location spatial

Table 6: Extracted topics and relevant keywords – continuation

fig, line, block, cell, column, row, space, region, red, color
tile, ill, tim, ion, el, ed, te, tion, arc, ca
effect, suggest, choice, expect, evidence, discuss, strong, attempt, issue, alternative
une, ce, est, pour, dan, par, les, qui, des, sont
program, element, computer, basic, linguistic, procedure, component, specification, concern, kind
dataset, art, split, accuracy, outperform, benchmark, challenge, bias, setup, tune
, ooo, oooo, , oo, ooooo, uooo, oo, uu, uuuu
precision, recall, match, detection, filter, extraction, threshold, detect, confidence, identification
keyword, title, conference, computational_linguistic, page, proceeding, tutorial, university, year, processing
german, read, incremental, reading, die, prime, processing, der, surprisal, field

Table 7: Excluded topics

B Top relationships

Task	Algorithm
Neural MT	RNNs
Reinforcement Learning	Plan-based Dialogue
Deep Learning	Neural MT
Unification	Grammars
Finite State Machines	Phonology
Plan-based Dialogue	Scene Description
Unification	Logical Forms
Semantic Role Labelling	Frame Semantics
Topic Models	Summarization
Discourse	Plan-based Dialogue

Table 8: Strongest friendship relations (task-algo).

Algorithm	Data
Statistical MT	Parallel Corpora
Transfer Learning	Parallel Corpora
Ontologies	Dictionaries
Reinforcement Learning	Social Media
Combinatory Categorical Grammar	Lexicons
Grammars	Lexicons
Plan-based Dialogue	Social Media
News Articles	Topic Models
Graphs	Knowledge Base
Constituent Parsing	Lexicons

Table 9: Strongest friendship relations (algo-data).

Task	Data
Multilinguality	Parallel Corpora
Stylistics	Social Media
Statistical MT	Parallel Corpora
Phonology	Dictionaries
Argument Mining	Social Media
Transliteration	Parallel Corpora
Multi-Word Expressions	Dictionaries
Unification	Lexicons
Named Entity Recognition	Knowledge Base
Morphology	Dictionaries
Opinion Mining	Social Media

Table 10: Strongest friendship relations (task-data).

Task	Task
Phonology	Semantic Role Labelling
Morphology	Discourse
Phonology	Anaphora/Coref. Resolution
Phonology	Relation Extraction
Phonology	Discourse
Discourse Segmentation	WordNet/Disambiguation
Events/temporal	Phonology
Speech Recognition	WordNet/Disambiguation
Statistical MT	Relation Extraction
Speech Recognition	Relation Extraction

Table 11: Strongest arms-race relations (task-task).

Algorithm	Algorithm
Topic Models	Dependency Parsing
Wordnet/Disambiguation	Dependency Parsing
Finite State Machines	Plan-based Dialogue
Wordnet/Disambiguation	Sequence Analysis
Topic Models	Statistical MT
Finite State Machines	Frame Semantics
Clustering	Statistical MT
Finite State Machines	Ontologies
Trees	Wordnet/Disambiguation
Statistical MT	Wordnet/Disambiguation

Table 12: Strongest arms-race relations (algo-algo).

Data	Data
Knowledge Base	Parallel Corpora
Lexicons	News Articles

Table 13: Strongest arms-race relations (data-data).

Task	Task
Unification	Neural MT
Disambiguation	Neural MT
Unification	Vector Spaces
Named Entity Recognition	Unification
Neural MT	Wordnet/Disambiguation
Sentiment Analysis	Unification
Unification	Summarization
Unification	Prediction
Unification	Language Models
Anaphora/Coreference Resolution	Neural MT

Table 14: Strongest head-to-head relations (task-task).

Algorithm	Algorithm
Grammars	Neural MT
Grammars	RNNs
Ontologies	Neural MT
Logical Forms	Neural MT
Neural MT	Wordnet/Disambiguation
Neural MT	Combinatory Categorical Grammar
Constituent Parsing	Neural MT
Finite State Machines	RNNs
Logical Forms	RNNs
Grammars	Deep Learning

Table 15: Strongest head-to-head relations (algo-algo).

Algorithm	Algorithm
Grammars	Neural MT
Grammars	RNNs
Ontologies	Neural MT
Logical Forms	Neural MT
Neural MT	Wordnet/Disambiguation
Neural MT	Combinatory Categorical Grammar
Constituent Parsing	Neural MT
Finite State Machines	RNNs
Logical Forms	RNNs
Grammars	Deep Learning

Table 16: Strongest head-to-head relations (algo-algo).

Data	Data
Lexicons	Knowledge Base
Knowledge Base	Dictionaries
Ontologies	Neural MT
Social Media	Parallel Corpora
Social Media	Lexicons

Table 17: Strongest head-to-head relations (data-data).

Algorithm	Algorithm
Reinforcement Learning	Neural MT
Statistical MT	Neural MT
Transfer Learning	Neural MT
Reinforcement Learning	RNNs
Dependency Parsing	Constituent Parsing
Neural MT	Dependency Parsing
RNNs	Sequence Analysis
Learning	Neural MT
Probabilistic	Neural MT
Clustering	Ontologies

Table 18: Strongest tryst relations (algo-algo).

Task	Task
Generation	Neural MT
Generation	Summarization
Statistical MT	Neural MT
Summarization	Neural MT
Vision/Multimodal	Scene Description
Phonology	Language Models
Neural MT	Transliteration
Summarization	Discourse
Textual Entailment	Vector Space
Summarization	Event Extraction

Table 19: Strongest tryst relations (task-task).

Data	Data
Dictionaries	Parallel Corpora
Lexicons	Parallel Corpora

Table 20: Strongest tryst relations (data-data).