Machine Extraction of Tax Laws from Legislative Texts

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Abstract

Using a corpus of compiled codes from U.S. states containing labeled tax law sections, we train text classifiers to automatically tag tax-law documents and, further, to identify the associated revenue source (e.g. income, property, or sales). After evaluating classifier performance in held-out test data, we apply them to an historical corpus of U.S. state legislation to extract the flow of relevant laws over the years 1910 through 2010. We document that the classifiers are effective in the historical corpus, for example by automatically detecting establishments of state personal income taxes. The trained models with replication code are published at https://github.com/luyang521/tax-classification.

1 Introduction

A foundational task in legal document analysis is to determine a document's area of legal practice – for example, tax law. In a law firm or court administrative office, distinguishing tax-related matters from others is necessary for assigning work to lawyers or judges who have the right expertise. In the scope of income reporting and payments, having the relevant statutes and cases to hand is necessary for complying with the law without overpaying. In empirical legal studies, measurement of the volume, complexity, or other features of tax laws is predicated on extracting those laws in the first place.

This essential task – of distinguishing different legal topics, such as which laws are about tax – has traditionally been done by hand. Tax law materials are assembled in books and databases by trained experts. Building and maintaining these materials is costly, especially in updating corpora to accommodate new material, such as newly enacted statutes. A cheaper and quicker approach would have broad benefits in private legal practice, in the courts, and in academic research.

This paper provides a method and tools for automatically tagging plain-text documents with their relevance to tax law. We use machine learning applied to the law texts to distinguish tax legislation from non-tax legislation in the jurisdictional context of U.S. states. Further, within the set of tax laws, we train a second model to classify the associated source – e.g. personal income, sales, property.

The approach works as follows. We start with a corpus of tax code sections, with class labels generated from section headers. The plain texts of the code sections are transformed to frequency distributions over a vocabulary of tens of thousands of phrases. Using those phrase frequencies as inputs, we train a binary text classifier to all statutes to predict the label of tax-related or not. We train a second multinomial classifier on the subset of tax law statutes to predict the tax source label – individual income tax, corporate income tax, property tax, etc. For the first binary classifier, we get the best performance with a regularized logistic regression (95% accuracy). For the multinomial source classifier, we get the best performance with a random forest classifier (73% accuracy).[1]

We then apply these classifiers to assign labels in an historical corpus of state session laws, issued biennially over the century starting in 1910 and ending in 2010. We validate that the model attends to tax-related language in the target corpus and is 90% accurate in a sample of sentences classified as tax-related or not. As an empirical validation, we show that the volume of legal texts related to personal income tax jumps up sharply in the bienniums when a state income tax is introduced, but there is no such jump for tax laws from other sources besides personal income.

Our classifier and this paper add to the growing

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[1] The open-source package, with the trained models and sample code, is available at https://github.com/luyang521/tax-classification.

literature in applied legal NLP (Palau and Moens, 2009; Kim et al., 2019; Alberts et al., 2020). More specifically, we add to the work on automated classification of relevant legal topics (e.g. Howe et al., 2019). Substantively, the paper is related to others focusing on tax law (Waltl et al., 2017; Sengupta and Dave, 2021). Besides their applications in industry, these text-based legal tools will be useful for empirical legal studies on taxation, such as Alarie et al. (2016) and Choi (2020).

2 Corpus Data

Our training corpus for learning to classify texts is a collection of compiled codes from U.S. states, obtained from LexisNexis in 2017. A document is a statute section. Each section is labelled for whether it is related to taxes or not. Within those related to taxes, we have additional labels for the category of taxation.

These labels were produced through a partly automated iterative process, overseen by a lawyer with U.S. legal training. First, we applied automated pattern matching on the legislative section headings to identify sections related to taxes.[2] The lawyer annotator inspected the associated statutes, and we refined the pattern matches until obtaining high precision and recall. Second, within the tax-related statutes, we produced another set of patterns to match different tax sources. These were also iteratively checked in conjunction with the lawyer annotator. Tax-related statutes that did not get assigned to a source are assigned to an Other category.

Table 1 shows the distribution of labels in the annotated dataset. Taxes are a substantial component of state codes at 6.9%, but the classification task is still quite unbalanced. Similarly, the tax sources are unbalanced, with the largest category (other) at 28.2% and the smallest category (license taxes) at 2.0%.

The application data set for analyzing flows of legislation is the State Session Laws for 1900-2010, obtained from HeinOnline. These are 2,506,513 statutes coming from the annual or biennial session laws enacted by U.S. states in any given year.

Table 1: Label Distribution in Source Data

A. Tax-Related or Not		
	Number of Sections	**Percentage**
Tax related	45468	6.87%
Not tax-related	616449	93.13%

B. Tax Source		
Tax source	**Number of Sections**	**Percent**
Corporate tax	2727	6.00%
Energy tax	3665	8.06%
Excise tax	7494	16.48%
Income tax	4768	10.49%
Inheritance tax	1259	2.77%
License tax	898	1.98%
Property tax	8591	18.90%
Sales tax	3229	7.10%
Other	12837	28.23%

The data come as raw OCR from document scans, with a sample shown in Appendix Table A.1. The data are segmented into statutes through an automated process. The resulting statute sections are not annotated as being related to taxes or not. In addition, they do not contain section headers, so using the header-based pattern matching approach is not feasible.

Before getting to the modeling, we build a joint vocabulary from the historical session laws and modern codes. In both corpora, we break down the plain text into countable features. Each statute section is represented as a frequency distribution over a vocabulary of words, bigrams (two-word phrases), and trigrams (three-word phrases). The vocabulary is filtered to the 50,000 most frequent words and phrases used in both corpora, after dropping any phrases appearing in more than 75% of documents.

3 Machine Extraction of Tax Laws

This section describes how we train a model to predict whether a statute section is tax related. We start with the annotated modern codes sections, and the n-gram features described above. The task is to train a text classifier to reproduce the annotated labels, extracted from the statute section headers, based on the statute body text. For evaluation, we split the set of codes into 80% training set and 20% test set.

For the machine classification, we experimented with two models: logistic regression and a random forest classifier (e.g. Friedman et al., 2001).[3]

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[2]Note that the pattern matching is applied to the full hierarchy of section headings, going from title to chapter to section. So for example, if the chapter is called "Taxation" and the section is called "Relief", that section would be coded as tax-related based on the higher-level chapter heading. Similarly, in the chapter on "Education", the section on "Education Tax" would be coded as tax-related but the section on "Teacher Training" would not.

[3]We also experimented with a convolutional neural net

For each of these models, we performed grid search to select hyperparameters with five-fold cross-validation in the training set. The selected settings are reported in Appendix Table A.2. One of the hyperparameters was the degree of additional feature selection within the training set using a chi-squared test. For example, for logistic regression, the model uses only the 2000 most predictive features, uses balanced class weights, and adds weak L2 regularization (penalty = .01).

Table 2: Performance of Tax-Law Classifiers

Model	Test Accuracy	Test AUCROC	Test F1	Test Precision	Test Recall
Logistic	0.952	0.901	0.552	0.783	0.427
Random Forest	0.950	0.889	0.503	0.790	0.368

Figure 1: Calibration Plot for Tax-Law Classifier

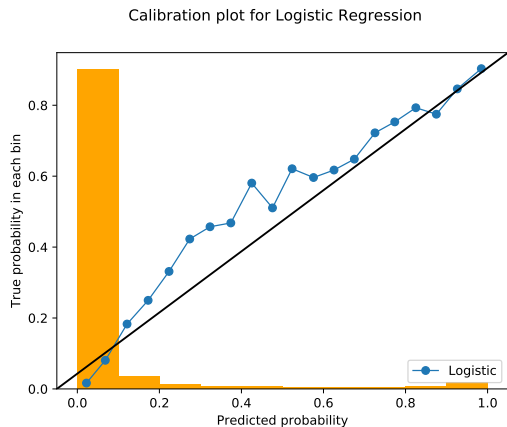Calibration plot for Logistic Regression

Table 2 reports the test-set evaluation results for the tax-law classifier. Performance is quite good for both classifiers, with logistic regression doing slightly better with test-set accuracy = .952, and AUC = .901. The model is somewhat conservative in identifying tax statutes (recall = .427), but with good precision (.783). In addition, the logistic regression model is well-calibrated (Figure 1), properly ranking statute sections by their probability of being about taxes, and faithfully replicating the test-set distribution. Finally, we assessed the qualitative validity of the classifier by analyzing the phrases that are most predictive of the label (Appendix Table A.3). They are quite intuitive, including "tax", "taxpayer", "tax imposed", "revenue", "department of revenue", and "assessor".

Thus, we are confident with the performance of the tuned logistic regression model, for the purposes of classifying documents as tax-related or not.

4 Classifying Tax Laws by Tax Source

The next task is to classify the source of taxed value. The corpus used is the set of annotated statute sections that were labeled as tax-related. Each statute is labeled according to one of the nine classes listed in Table 1 Panel B. We do stratified sampling to preserve the class distribution across train (80%) and test (20%) set.

Logistic regression performed poorly on this task, so we focus on the random forest classifier.[4] Again, hyperparameters were selected through five-fold cross-validated grid search (Appendix Table A.4). We have a feature set of 10K n-grams, balanced class weights, and 500 decision trees in the ensemble.

Table 3: Performance of Tax-Source Classifier

A. Overall Performance				
Model	Test Acc.	Test F1	Test Prec.	Test Recall
Random Forest	0.728	0.728	0.745	0.728

B. Performance by Class			
	Precision	Recall	F1-score
Corporate tax	0.71	0.47	0.56
Energy tax	0.87	0.71	0.78
Excise tax	0.82	0.71	0.76
Income tax	0.79	0.73	0.76
Inheritance tax	0.82	0.74	0.78
License tax	0.96	0.76	0.85
Property tax	0.76	0.7	0.73
Sales tax	0.78	0.67	0.72
Other	0.61	0.83	0.71

Table 3 Panel A reports the aggregate metrics for classifying tax source labels. The accuracy is 73%, with a weighted average precision of .75. Unsurprisingly, the source classifier is less accurate than the earlier binary classifier. It has to decide between nine classes with significant overlap in language.

Looking at the metrics separately by class, Panel B shows that precision is quite high across all classes, but recall varies significantly. For example, income tax has a precision of .79 and recall of .73, while sales tax has a precision of .78 and recall of

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applied to word embeddings. This approach performed significantly worse than the logistic regression and random forest, so we do not report the results. Exploring the gains from neural nets in this task is an important area for future work.

[4]As mentioned in the footnote above, we also tried a convolutional neural net model, which performed even worse than logistic regression.

.67. The highest-recall category "Other", is also the lowest-precision. This means that the classifier is somewhat conservative in identifying particular tax sources and often errs by putting documents in the "other" bin.

For a qualitative assessment, Appendix Table A.5 shows the set of words and n-grams that the model most associates with each tax-source class. They are quite intuitive – for example, "gasoline" and "fuel" are associated with energy, "cigarettes" with excise, "decedent" with inheritance, and "property" with property. Overall, these phrases suggest that the classifier is capturing legally relevant features, rather than correlated features.

5 Application to State Session Laws

We now have two trained text classifiers. One can distinguish legislative documents related to tax law from legislative documents on other legal areas. The second one can take documents related to tax law and tell use the value source from which the tax is derived. Now we show the usefulness of these classifiers by applying them to an historical corpus of 2.5M state session laws.

Table 4: Distribution of Labels in State Session Laws

A. Tax Related		
	Number of statutes	Percent
Tax related	108109	4.31%
Not tax-related	2398404	95.69%

B. Source Proportions		
Tax source	Tax-related	Not tax-related
Corporate tax	2.48%	0.43%
Energy tax	5.94%	1.03%
Excise tax	9.30%	5.90%
Income tax	10.92%	0.72%
Inheritance tax	1.87%	0.76%
License tax	0.57%	0.11%
Property tax	28.57%	7.01%
Sales tax	9.83%	0.75%
Other	30.52%	83.29%

For each statute, we form a predicted probability that it is about taxes using the first tax detection model, trained on the modern codes. We take as tax laws the set of statutes that have a greater than 50% chance of being part of the tax code. The resulting labels are tabulated in Table 4 Panel A. We find that about 4.3% of statutes are about taxes, not too far from the 6.9% of sections observed in the modern codes. The proportion of statutes about taxes has not greatly changed over time, which is reassuring

that even though we use modern statutes to train the model, the resulting predictions should be valid even for the early historical years of the statutes.

To obtain some qualitative confidence in the classifier, we applied it at the sentence level for a large sample of statute sections. We then ranked the sentences by predicted probability of being tax related. Appendix Table A.6 shows the top-20 sentences in the sample by predicted class probability on tax-related; Appendix Table A.7 shows an equivalent list but filtering out sentences containing the string "tax". The retrieved sentences are clearly and definitively related to tax law, and the assignment does not depend on the presence of the word "tax". For comparison, Appendix Table A.8 shows the 20 sentences with the lowest class probability (so least likely to be tax-related). On an inspection, these don't mention anything related to taxes, and tend to have more of a focus on courts and judicial issues.

For a more comprehensive evaluation about the cross-domain accuracy, we sampled 100 sentences from the historical corpus, 50 from each predicted class (tax-related or not). The lawyer annotator performed a blind tagging of the sentences as tax-related or not-tax-related.[5] The manual annotations matched the model predictions in 90% of the observations, quite close to the accuracy from the original domain.

Next, the tax-source classifier is applied to the documents in the historical state session laws and class predictions are formed. Table 4 Panel B shows the distribution across classes. In the Tax-Related column, the relative frequencies roughly match up to the distribution in the 2017 codes, with for example 29% about property tax and 11% about income tax. For comparison, the third column shows the predicted tax-source probabilities for the statutes classified as not tax related. A full 83% of these documents are put into the "Other" category, reflecting that these statutes tend not to contain tax-related content that would allow the tax-source model to classify them.[6]

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[5]The annotator's task was to answer the question: "Is this sentence making a rule related to taxation, or is it part of the state tax law?" Note that it is often unclear from a single sentence how to answer this question, so the annotator made a best guess. Performance metrics based on reading longer documents, such as sections or chapters, may be different. We have not evaluated performance longer documents given the significant annotation resources required.

[6]We attempted to evaluate the performance of the tax-source classifier at the sentence level, as done with the tax-related classifier. However, we found that the source classifier does not work well on the sentence level. There is not enough

As a final validation step, we check that the introduction of a new tax system – the state personal income tax – is reflected in the measurements generated by our classifiers. We have records of the years where each U.S. state first collected a state income tax. We assess the dynamic impact of the introduction of the tax on the legislative output across tax sources. If our classifier is working well, we would expect a sharp and substantial jump in income-tax legislation at the time of these reforms. We would expect no significant change in tax legislation on other sources besides personal income.

To test these expectations, we estimate a panel event study model with distributed lags and leads by biennium (Schmidheiny and Siegloch, 2019), with state and biennium fixed effects and standard errors clustered by state. Because we would expect that legislation could be passed in the biennium before the tax was first collected, the coefficients are estimated relative to two bienniums before the introduction of the tax. We look at two outcomes. First, we use the log number of words in statutes classified as tax-related and related to income tax. Second, we use the log number of words in statutes classified as tax-related but related to any tax source besides income tax.
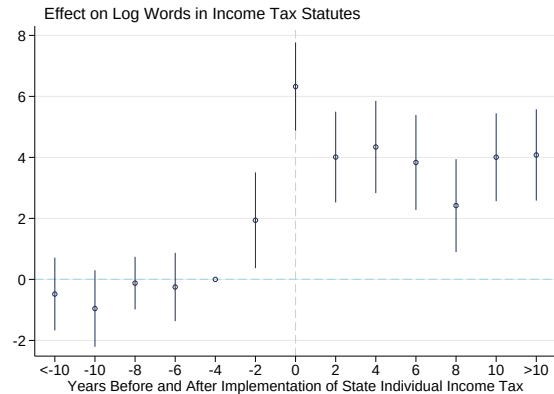
Figure 2 Panel A shows the coefficients and 95% confidence intervals from the first panel event study regression. We can see that there is a clear jump in income-tax legislation text in the biennium before the tax introduction, which increases even more drastically in the biennium where income taxes are first collected (a six log points increase). The effect on flow of legislation gradually decreases but remains consistently positive and statistically significant, reflecting that additional legislation is needed to maintain and clarify the policy – for example, to update rates, to add exemptions, and to close statutory loopholes.

Meanwhile, Figure 2 Panel B shows the equivalent event study effect on tax-related legislation for *other* tax sources besides income tax. There is no effect at all on this outcome, as expected for a placebo test. Together, the event study regressions indicate that the tax classifier is precisely capturing
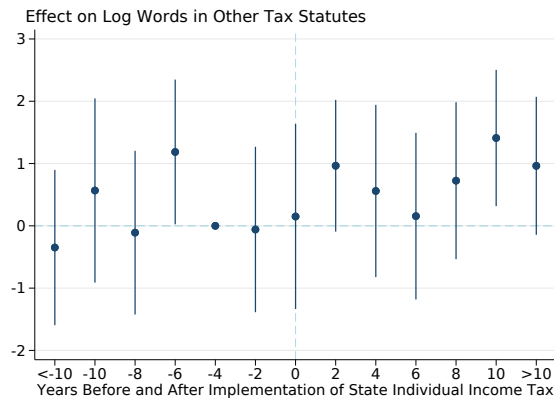
information in a single sentence to make a confident determination, and the resulting top-ranked classes are noisy and mostly incorrect. The source classifier requires longer documents, such as full statute sections. We did not have sufficient annotation resources for a trained lawyer to read lengthy statute documents and determine a single tax source. Further evaluation in application domains could be considered in future work.

Figure 2: Effect of State Income Tax on Income Tax Legislation

A. Main Effect on Income Tax Legislation

Effect on Log Words in Income Tax Statutes

Years Before and After Implementation of State Individual Income Tax

B. Placebo Effect on Other-Source Tax Legislation

Effect on Log Words in Other Tax Statutes

Years Before and After Implementation of State Individual Income Tax

the income-tax components of historical statutes, and not other potentially correlated components.

6 Conclusion

In this paper, we have introduced a classifier for identifying tax laws in legislative corpora, and a second classifier for identifying the source within the set of tax laws. The approach uses a ground-truth corpus of U.S. state codes labelled based on the statute section headers and a random forest classifier applied to n-gram representations of the documents. The trained classifiers perform well in the original domain according to the standard test-set performance metrics.

We provide trained models and code as an open-source package for the research community. In an application, we illustrate how to use the trained model in a new domain – a century of historical statutes from U.S. states. A number of validation steps provide confidence in the usefulness of the classifier for this application and others, whether in the legal tech industry or in empirical legal scholar-

ship.

Notwithstanding the promising results from these validations, our approach for classifying tax laws has a number of limitations which could be addressed in future work. First, the model is trained and validated only for U.S. state legislation. It is unclear whether it would work for federal or local legislation in the United States, and it is unlikely the model would work well in other countries. Extending the approach to other jurisdictions would present a clear and straightforward benefit. It could also be fruitful to experiment with models that work across jurisdictions, perhaps including metadata on the jurisdiction.

Second, the approach has been limited to classical machine learning models and has not used deep learning. While our initial experimentation with convolutional neural nets have been unsuccessful, there is clearly additional room for performance gains using state-of-the-art models, especially transformers (e.g. Liu et al., 2019; Wolf et al., 2020). A difficulty with the standard transformer models is the maximum context length, which is shorter than many statute documents. That difficulty might be addressed by creative document segmenting, or by adopting the newer generation of long-document transformers that use sparse attention (e.g. Zaheer et al., 2020).

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A Appendix

Table A.1: Example of Text: Statute 761 from the 767 Volume of California's State Law (1990)

> SEC. 3.5. +} Section 23603 of the Revenue and Taxation Code is amended to read: 23603. (a) For income years beginning on or after January 1, 1991, and before January 1, 1996, there shall be allowed as a credit against the "tax" (as defined by Section 23036) an amount equal to 55 percent of the qualified cost paid or incurred by the taxpayer for low-emission vehicles or low-emission conversion devices. The credit allowed by this section shall be claimed in the income year the device is installed or, in the case of a new low-emission motor vehicle, the income year the low-emission vehicle is placed in service, and shall not exceed one thousand dollars ($1,000) per automobile, motorcycle, or two person passenger vehicle, or three thousand five hundred dollars ($3,500) for a vehicle whose weight is in excess of 5,750 pounds.

Table A.2: Hyperparameters selected: Tax-Law Classifiers

Model	Features Selected by Chi Square Selector	Hyperparameters Selected
Logistic Regression	2000	class weight : 'balanced' penalty : 'l2' inverse of regularization strength C : 100
Random Forest	30,000	class weight : 'balanced' max features: 35 max depth: 50 number of estimators: 800

Table A.3: Text Features Associated with Tax-Related Classifier

tax, taxpay, tax_impos, depart_of_revenu, exempt, assess, taxabl, taxabl_year, collect, privileg_tax, tax_credit, tax_levi, such_tax, tax_year, taxat, sale, for_the_taxabl_year, tax_liabil, amount_of_tax, taxpay_shall, revenu

Table A.4: Hyperparameters selected in Tax-Source Classifier

Model	Features Selected by Chi Square Selector	Hyperparameters Selected
Random Forest	10,000	class weight : 'balanced' max features: 50 max depth: 100 number of estimators: 500

Table A.5: Text Features Associated with Tax-Source Class Predictions

				Tax Sources			
Corporate	**Energy**	**Excise**	**Income**	**Inheritance**	**License**	**Property**	**Sales**
incom_year	gasolin	ani	taxpay	deced	licens_tax	ani	tangibl_person_properti
section	ani	cigarett	ani	inherit_tax	privileg_tax	assessor	ani
taxpay	motor_fuel	tax	section	estat	ani	section	sale
ani	fuel	section	of_the_intern_revenu	ani	act_to	tax	sale_and_use_tax
franchis_tax	special_fuel	stamp	taxabl_year	estat_tax	gross_receipt	properti	section
of_the_intern_revenu	distributor	tax_impos	incom	tax	virginia	year	retail
corpor	section	state	code	feder_estat_tax	privileg_licens	counti	tax
state	state	provis	adjust_gross_incom	section	busi	assess	sale_tax
net_incom	sever_tax	act_to	gross_incom	death_tax	privileg	act_to	state
tax	tax	nineteen_hundr	incom_tax	death	code	taxat	use_tax

Table A.6: Sentences in State Session Laws with High Class Probability on Tax-Related

State	Year	Sentence
HI	1987	If the taxpayer is married at the close of the taxable year, the credit shall be allowed under subsection (a) only if the taxpayer and the taxpayers spouse file a joint return for the taxable year.
CA	1979	(d) For purposes of this section, except in the case of a husband and wife who live apart at all times during the taxable year, if the taxpayer is married at the close of the taxable year, the credit provided by this section shall be allowed only if the taxpayer and his spouse file a joint return for the taxable year.
FL	1977	The term "estimated tax" shall mean the amount the taxpayer estimates to be his tax under this part for the taxable year.
NM	1977	The credit provided by this section may be deducted from the taxpayers New Mexico income tax liability for the taxable year.
FL	1984	The amount of emergency excise tax paid or accrued as a liability to this state under chapter 221 which tax is deductible from gross income in the computation of taxable income for the taxable year.incurred for the taxable year which is equal to the amount of the credit allowable for the taxable year.
MN	2011	For individuals, the term "estimated tax" means the amount the taxpayer estimates is the sum of the taxes imposed by chapter 290 for the taxable year.
OK	1989	The Tax Commission shall deduct from any income tax refund due to a taxpayer the amount of delinquent state tax, and penalty and interest thereon.
GA	1977	If the taxpayer is married at the close of the taxable year, the credit shall be allowed under subsection (a) only if the taxpayer and his s5pose file a joint return for the taxable year."
KY	1974	(a) T]the amount of federal income tax actually paid or accrued for the taxable year on taxable income as defined in Section 63 of the Internal Revenue Code, and taxed under the provisions of this chapter.
CA	1939	Income Tax Act in the gross income of such person for the taxable year in which or with which the taxable year of the taxpayer ends; and.
NC	2005	The Secretary of Revenue shall determine from all available evidence the taxpayers correct tax liability for the taxable year.
AZ	2005	If the taxpayer has attained the age of sixty-five before the close of the taxable year filing a separate or joint return and the taxpayer is not claimed as a dependent by another taxpayer.2.
FL	1985	(2) The tax imposed by this section shall be an amount equal to 5 1/2 percent of the taxpayers net income for the taxable year.
CA	1979	(2) If the taxpayer is married at the close of the taxable year, the credit shall be allowed under subdivision (a) only if the taxpayer and his spouse file a joint return for the taxable year.
CA	1979	(5) (A) Except in the case of a husband and wife who live apart at all times during the taxable year, if the taxpayer is married at the close of the taxable year, the exclusion provided by this subdivision shall be allowed only if the taxpayer and his spouse file a joint return for the taxable year.
NM	1977	(4) the credit provided by this section may be deducted from the taxpayers New Mexico income tax liability for a taxable year ending in 1976.
NM	1977	(4) the credit provided by this section may be deducted from the taxpayers New Mexico income tax liability for a taxable year ending in 1977.
IN	2007	A taxpayer is entitled to a credit against the taxpayers state tax liability for a taxable year in an amount equal to fifty percent (50%) of the costs incurred by the taxpayer during the taxable year for providing a qualified wellness program for the taxpayers employees during the taxable year.
OR	2009	(A) For [himself or herself] the taxpayer if [he or she] the taxpayer is blind at the close of the taxable year; and.
NM	1977	The credit provided by this section may only be deducted from the taxpayers New Mexico income tax liability for the taxable year in which the equipment was installed on the taxpayers property.

Table A.7: Sentences in State Session Laws with High Class Probability on Tax-Related, Not Mentioning "Tax"

State	Year	Sentence
UT	2000	(3) The county auditor shall record the assessment upon the assessment books in the same manner provided under Section 59-2-1011 in the case of a correction made by the county board of equalization, and no county board of equalization or assessor may change any assessment so fixed by the commission.
AZ	1989	Upon preparation of he rolls, the assessor shall apply the appropriate percentage to the full cash value and limited property value of all property so that the assessel valuation will be shown.
UT	2008	(4) (a) Before the county board of equalization grants any application for exemption or reduction, the county board of equalization may examine under oath the person or agent making the application.
UT	2008	(b) The value fixed by the assessor may not be reduced by the county board of equalization or by the commission.
UT	1992	The value fixed by the assessor may not be reduced by the county board of equalization or by the commission.
CA	1992	All real property not already assessed up to the 1975-76 full cash value may be reassessed to reflect that valuation.
CA	1979	STrATUTES OF 1979. ownership of real property occurs, the assessor shall reappraise such real property at its full cash value.
AZ	1985	Upon preparation of the rolls, the assessor shall apply the appropriate percentage to the full cash value and limited property value of all property so that the assessed valuation will be shown.
FL	1998	(a) Review and approve all budgets and recommended budget amendments in the Florida state community college system.
CA	1941	In determining the actual value" of intangible personal property, the assessor shall not take into account the existence of ally custom or common method, if any, in arriving at the full cash value of any class or classes of property.SEC.
UT	2000	(21) "Use," as used in Part 3, Special Fuel, means the consumption of special fuel for the operation or propulsion of a motor vehicle upon the public highways of the state and includes the reception of special fuel into the fuel supply tank of a motor vehicle.
HI	1956	(e) In the determination of the basis or adjusted basis of any stock, securities or other property.
NE	2004	(4) In any year, the county assessor or the county board of equalization may cause a review of any exemption to determine whether the exemption is proper.
CA	1939	of any county determine that, in order to equalize the assessment of property within the county, an appraisal of all or any class of property is required, the clerk of the board of supervisors and the assessor shall certify this determination to the State Board of Equalization.
MT	1989	The department may request additiinal federal authority for work training programs through the budget amendment process.
MT	1989	the outbreak is an emergency for budget amendment purpnses under 17-7.401 through If the department dies not have sufficient resources to perform the 10-year brand rerecord as required by 81-3-104. the lak if resources is an emergency for budget amendment purposes under 17.7-401 through 17.7-405.
AZ	1989	A person who owns, controls or possesses property valued by the county assessor may each year designate an agent to act on his behalf on any matter relating to the review of the valuation of the property before the assessor and the county board of equalization.
UT	2008	(2) The county board of equalization shall notify an owner of exempt property that has previously received an exemption but failed to file an annual statement in accordance with Subsection (9)(c), of the county board of equalizations intent to revoke the exemption on or before April 1.
UT	1992	(7) "Use," as used in Part 3, means the consumption of special fuel for the operation or propulsion of a motor vehicle upon the public highways of the state and includes the reception of special fuel into the fuel supply tank of a motor vehicle.
NE	2007	Only the county assessor may appeal the grant of such an exemption by a county board of equalization.

Table A.8: Sentences in State Session Laws with Low Class Probability on Tax-Related

State	Year	Sentence
UT	2000	(i the registered agent of the corporation, if the notice or certificate is required to be mailed to the registered agent; or.
HI	2009	[(a)] A registered agent of a domestic or foreign limited liability company may resign from the registered agents appointment by [signing and delivering to the directe for filing the signed statement Of resignation.
CA	1992	(c) If the child is the subject of a guardianship petition, the adoption petition shall so state and shall include the caption and docket number or have attached a copy of the letters of the guardianship or temporary guardianship.
ID	1979	(f) That the address of its registered office and the address of the business office of its registered agent, as changed, will be identical.
CO	1967	The provisions of this subsection (4) shall in no way affect the right of a corporation to file a statement of change of registered office or registered agent as provided in subsection (1) of this section.
AZ	2005	(a) IF THE DISCLAIMANT IS AN INDIVIDUAL, THE DISCLAIMED INTEREST PASSES AS IF THE DISCLAIMANT HAD DIED IMMEDIATELY BEFORE THE TIME OF DISTRIBUTION.
HI	2009	(d) A commercial registered agent shall promptly furnish each entity represented by it with notice in a record of the filing of a statement of change relating to the name or address of the agent and the changes made by the filing.
GA	1955	Whenever a general court-martial is reduced below five members, the trial shall not proceed unless the convening authority appoints new members sufficient in number to provide not less than five members.
UT	2000	Mi the registered agent of the limited liability company Lat Rh; addres -at forth in the limited Umitedmembers.
AZ	1985	THE COURT THAT ISSUED THE SUPPORT ORDER LACKED PERSONAL JURISDICTION OVER THE OBLIGOR.3.
HI	2011	failure to file[-] ar record[- -registef] the disclaimer does not affect its validity as between the disclaimant and persons to whom the property interest or power passes by reason of the disclaimer."
KY	1974	(I) The registered agent so appointed by a corporation shall be agent of such corporation upon whom any process, notice or demand required or permitted by law to be served upon the corporation may be served.
ME	1915	Special courts-martial may consist of any number of officers from three to five, inclusive.-summary.
IL	2003	The court shall condition the appointment of the confidential intermediary on the petitioners payment of the intermediarys fees and expenses in advance of the commencement of the work of the confidential intermediary.
VA	2000	(d) The warranty under this section is not subject to the preclusion in SS 59.1-501.13(a) (1) on disclaiming diligence, reasonableness, or care.
CA	1992	(b) A support order made in this state may also be registered pursuant to Sections 4849 to 4853, inclusive, in any county in which either the obligor or the child who is the subject of the order resides.
CO	1993	(1) AS LONG AS THIS STATE REMAINS THE RESIDENCE OF THE OBLIGOR, THE INDIVID-UAL OBLIGEE, OR THE CHILD FOR WHOSE BENEFIT THE SUPPORT ORDER IS ISSUED; OR.
CA	1992	(1) If the support order was issued by a court of this state, perfect an appeal to the proper appellate court.
AZ	2008	The court may establish a permanent guardianship between a child and the guardian if the prospective guardianship is in the childs best interests and all of the following apply.1.
MI	2002	(p) Disclaiming or limiting the implied warranty of merchantability and fitness for use, unless a disclaimer is clearly and conspicuously disclosed.