

Configuration Manual for Enhancing Risk Assessment in Legal Documents Through Advanced Machine Learning

MSc Research Project MSc Data Analytics

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MSc Project Submission Sheet

School of Computing

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Module:	Configuration Manual				
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I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project. ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action. Sai Teja Pusarla Signature: 12-12-2024 Date: PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST					
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Configuration Manual

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1. Introduction

This manual outlines a step-by-step replication guide for Assessing Risk whether it's Risky or Not Risky and Anomaly detection using advanced machine learning models. The experiment compares several models, including BERT, Legal BERT, Isolation Forest whereby Legal BERT surpasses other in accuracy and error minimization. This document lists the packages and configurations of software for the experimental environment so that it can replicate similar results.

2. Deployment Environment

2.1 Hardware Specification

• **Processor:** Intel Core i5 or equivalent

• **RAM:** 8 GB or higher

• **GPU:** Min 2 cores or higher.

2.2 Software Specification

- Operating System: Windows 10/11, macOS, or Linux-based OS
- **Programming Language:** Python 3.11
- **IDE:** Jupyter Notebook or VS Code (with Python extension)

2.3 Core Libraries:

- os: For file and directory related work.
- torch: Used to implement BERT and Legal-BERT architectures.
- PyPDF2: For reading and extracting text from pdfs.
- pyrna: To deal with tabular data
- numpy: For numerical calculations.
- seaborn and matplotlib: For visualisation of data.

2.4 Machine Learning and NLP:

- torch. nn. functional: Used for activation functions and computing loss.
- torch. utils. data: This is used to create DataLoader and TensorDataset.
- transformers: For all things model and tokenizer, pre-trained on BERT, Legal-BERT, etc.
- scikit-learn: For model evaluation, PCA, train-test split and anomaly detection
- imbalanced-learn performing the oversampling (SMOTE) to deal with the class imbalance.

2.5 Additional Tools:

• huggingface-hub — to download pre-trained models e.g. BERT, Legal-BERT

2.6 Download the Required Files:

Place the following files in the project directory:

- master_clauses.csv (used in risk assessment)
- Legal_docs.csv (used in anomaly detection)

You need to install the following packages to execute this code

```
!pip install pandas
!pip install matplotlib
!pip install scikit-learn
!pip install numpy
!pip install PyPDF2
!pip install tqdm
!pip install transformers
!pip install torch
```

3. Configuration for Risk Assessment

3.1 Open the Notebook:

Open the file Risk Assessment.ipynb in Jupyter Notebook.

3.2 Prepare the Dataset:

- Ensure **master_clauses.csv** is in the same directory as the notebook.
- Update the file path in the code if needed:

```
# Load the dataset
file_path = "master_clauses.csv" |
data = pd.read_csv(file_path)

# Display basic information about the dataset
print("Dataset Columns:", data.columns.tolist())
print("Total Rows:", len(data))
print("NSample Data:")
print(data.head())
```

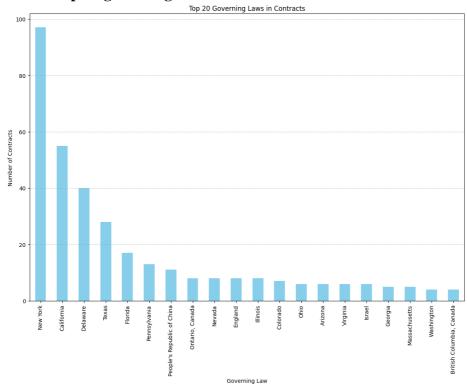
• To see the structure of dataset I'm printing the first few rows

]:	Filename	Document Name	Document Name- Answer	Parties	Parties-Answer	Agreement Date	Agreement Date- Answer	Effective Date	Effecti Da Answ
0	CybergyHoldingsInc_20140520_10-Q_EX- 10.27_8605	['MARKETING AFFILIATE AGREEMENT']	MARKETING AFFILIATE AGREEMENT	['BIRCH FIRST GLOBAL INVESTMENTS INC.', 'MA',	Birch First Global Investments Inc. ("Company"	['8th day of May 2014', 'May 8, 2014']	5/8/14	['This agreement shall begin upon the date of	N
1	EuromediaHoldingsCorp_20070215_10SB12G_EX- 10.B	['VIDEO-ON- DEMAND CONTENT LICENSE AGREEMENT']	VIDEO-ON- DEMAND CONTENT LICENSE AGREEMENT	['EuroMedia Holdings Corp.', 'Rogers', 'Rogers	Rogers Cable Communications Inc. ("Rogers"); E	['July 11 , 2006']	7/11/06	['July 11 , 2006']	7/11/
2	FulucaiProductionsLtd_20131223_10-Q_EX- 10.9_83	['CONTENT DISTRIBUTION AND LICENSE AGREEMENT']	CONTENT DISTRIBUTION AND LICENSE AGREEMENT	['Producer', 'Fulucai Productions Ltd.', 'Conv	CONVERGTV, INC. ("ConvergTV"); Fulucai Product	['November 15, 2012']	11/15/12	['November 15, 2012']	11/15/
3	GopageCorp_20140221_10-K_EX- 10.1_8432966_EX-10	['WEBSITE CONTENT LICENSE AGREEMENT']	WEBSITE CONTENT LICENSE AGREEMENT	['PSiTech Corporation', 'Licensor', 'Licensee'	PSiTech Corporation ("Licensor"); Empirical Ve	['Feb 10, 2014']	2/10/14	['Feb 10, 2014']	2/10/
4	IdeanomicsInc_20160330_10-K_EX- 10.26_9512211_E	['CONTENT LICENSE AGREEMENT']	CONTENT LICENSE AGREEMENT	['YOU ON DEMAND HOLDINGS, INC.', 'Licensor', '	Beijing Sun Seven Stars Culture Development Li	['December 21, 2015']	12/21/15	['December 21, 2015']	12/21/

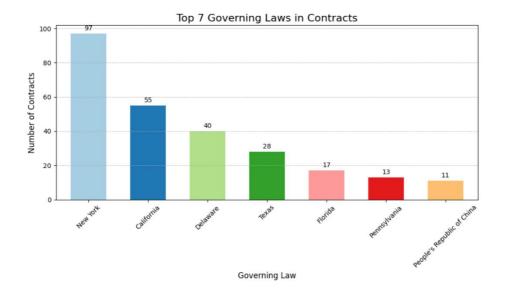
5 rows × 83 columns

3.3 Exploratory Data Analysis:

• Top 20 governing laws in contracts



• Top 7 Governing laws in contracts



• Replace '[]' with NaN

Date- Answer	Effective Date	Effective Date- Answer	Expiration Date	 Liquidated Damages	Liquidated Damages- Answer	Warranty Duration	Warranty Duration- Answer	Insurance	Insurance- Answer	Covenant Not To Sue		Third Party Beneficiary	Third Party Beneficiary- Answer
5/8/14	['This agreement shall begin upon the date of	NaN	['This agreement shall begin upon the date of	 NaN	No	["COMPANY'S SOLE AND EXCLUSIVE LIABILITY FOR T	Yes	NaN	No	NaN	No	NaN	No
7/11/06	['July 11 , 2006']	7/11/06	['The term of this Agreement (the "Initial Ter	 NaN	No	NaN	No	NaN	No	NaN	No	NaN	No
1/15/12	['November 15, 2012']	11/15/12	NaN	 NaN	No	NaN	No	NaN	No	NaN	No	NaN	No
2/10/14	['Feb 10, 2014']	2/10/14	['The initial term of this Agreement commences	 NaN	No	NaN	No	NaN	No	NaN	No	NaN	No
12/21/15	['December 21, 2015']	12/21/15	['The Term of this Agreement (the "Term") shal	 NaN	No	NaN	No	NaN	No	NaN	No	NaN	No

• Displaying top 10 common documents

Display the frequency of the top 10 most common document names
top_document_names = master_clauses_df['Document Name-Answer'].value_counts().head(10)
print(top_document_names)

Document Name-Answer SPONSORSHIP AGREEMENT 20 STRATEGIC ALLIANCE AGREEMENT 16 ENDORSEMENT AGREEMENT 14 Strategic Alliance Agreement 12 DISTRIBUTOR AGREEMENT 12 CO-BRANDING AGREEMENT 12 JOINT FILING AGREEMENT 12 AGENCY AGREEMENT 12 INTELLECTUAL PROPERTY AGREEMENT 10 CONSULTING AGREEMENT 10 Name: count, dtype: int64

Date Filtering and Year Extraction

```
format = "%m/%d/%y"

# Create a mask to filter rows with a specific date format

# Example: If you want to ensure that the format matches "%m/%d/%y", use regex or pd.to_datetime with errors='coerce'

mask = master_clauses_df['Agreement Date-Answer'].str.match(r"^\d{1,2}/\d{2}$", na=False)

# Apply the mask to filter the dates
filtered_dates = master_clauses_df['Agreement Date-Answer'].loc[mask]

# Convert dates to the desired year format

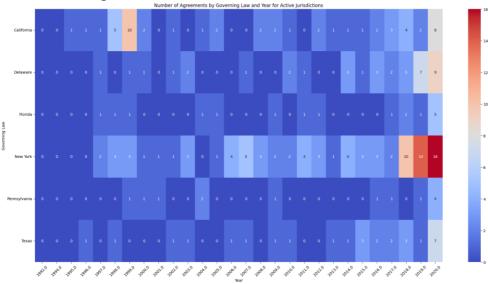
master_clauses_df['Agreement Year'] = pd.to_datetime(filtered_dates, errors='coerce', format=format).dt.year

# Check for unique years and nulls
print(master_clauses_df['Agreement Year'].unique())
print(master_clauses_df['Agreement Year'].isnull().sum()) # Check how many failed to parse
```

Output:

```
[2014. 2006. 2012. 2015. 1999. 2000. 2013. 2005. 2019. 2018. 2020. 2017. 2008. 2016. nan 2009. 2001. 2003. 2007. 2011. 2010. 2004. 1994. 1998. 2002. 1997. 1992. 1995. 1996. 1990.]
```

• Heatmap:



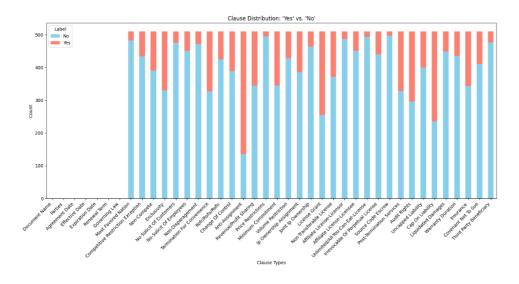
• Analysis and Export of Cleaned Clause Distribution Data

	No	Yes
Document Name	0.0	0.0
Parties	0.0	0.0
Agreement Date	0.0	0.0
Effective Date	0.0	0.0
Expiration Date	0.0	0.0
Renewal Term	0.0	0.0
Governing Law	0.0	0.0
Most Favored Nation	482.0	28.0
Competitive Restriction Exception	434.0	76.0
Non-Compete	391.0	119.0
Exclusivity	330.0	180.0
No-Solicit Of Customers	476.0	34.0
No-Solicit Of Employees	451.0	59.0
Non-Disparagement	472.0	38.0
Termination For Convenience	327.0	183.0
Rofr/Rofo/Rofn	425.0	85.0
Change Of Control	389.0	121.0
Anti-Assignment	136.0	374.0
Revenue/Profit Sharing	344.0	166.0
Price Restrictions	495.0	15.0
Minimum Commitment	345.0	165.0
Volume Restriction	428.0	82.0
Ip Ownership Assignment	386.0	124.0
Joint Ip Ownership	464.0	46.0
License Grant	255.0	255.0
Non-Transferable License	372.0	138.0
Affiliate License-Licensor	487.0	23.0
Affiliate License-Licensee	451.0	59.0
Unlimited/All-You-Can-Eat-License	493.0	17.0
Irrevocable Or Perpetual License	440.0	70.0
Source Code Escrow	497.0	13.0
Post-Termination Services	328.0	182.0
Audit Rights	296.0	214.0
Uncapped Liability	399.0	111.0
Cap On Liability	235.0	275.0
Liquidated Damages	449.0	61.0
Warranty Duration	435.0	75.0
Insurance	343.0	167.0
Covenant Not To Sue	410.0	
Third Party Beneficiary	477.0	33.0

• Balancing Data by Filtering Based on Label Threshold

	No	Yes
Competitive Restriction Exception	434.0	76.0
Non-Compete	391.0	119.0
Exclusivity	330.0	180.0
No-Solicit Of Customers	476.0	34.0
No-Solicit Of Employees	451.0	59.0
Non-Disparagement	472.0	38.0
Termination For Convenience	327.0	183.0
Rofr/Rofo/Rofn	425.0	85.0
Change Of Control	389.0	121.0
Anti-Assignment	136.0	374.0
Revenue/Profit Sharing	344.0	166.0
Minimum Commitment	345.0	165.0
Volume Restriction	428.0	82.0
Ip Ownership Assignment	386.0	124.0
Joint Ip Ownership	464.0	46.0
License Grant	255.0	255.0
Non-Transferable License	372.0	138.0
Affiliate License-Licensee	451.0	59.0
Irrevocable Or Perpetual License	440.0	70.0
Post-Termination Services	328.0	182.0
Audit Rights	296.0	214.0
Uncapped Liability	399.0	111.0
Cap On Liability	235.0	275.0
Liquidated Damages	449.0	61.0
Warranty Duration	435.0	75.0
Insurance	343.0	167.0
Covenant Not To Sue	410.0	100.0
Third Party Beneficiary	477.0	33.0

• "Yes" and "No" counts for all clauses



• Preparation and Split of Dataset for Non-Compete Clause Classification

Training samples: 408 Testing samples: 102

• BERT Model Setup and Data Preparation for Training

Train Dataset Size: 408 Test Dataset Size: 102

BERT Model Training with Class Weighting and Learning Rate Scheduling

```
Epoch 1/15
Epoch 1: 100% Accuracy: 0.6814
                                            | 51/51 [01:02<00:00, 1.22s/it, accuracy=0.681, loss=0.456]
Epoch 2/15
Epoch 2: 100%
                                            | 51/51 [01:00<00:00, 1.19s/it, accuracy=0.738, loss=0.496]
Epoch 2 Loss: 0.6531 | Accuracy: 0.7377
Epoch 3/15
Epoch 3: 100%
                                            | 51/51 [00:58<00:00, 1.14s/it, accuracy=0.723, loss=0.241]
Epoch 3 Loss: 0.6020 | Accuracy: 0.7230
Epoch 4/15
Epoch 4: 100%
                                            51/51 [01:03<00:00, 1.25s/it, accuracy=0.752, loss=0.581]
Epoch 4 Loss: 0.5641 | Accuracy: 0.7525
Epoch 5/15
                                            51/51 [01:03<00:00, 1.24s/it, accuracy=0.772, loss=0.538]
Epoch 5: 100%
Epoch 5 Loss: 0.5113 | Accuracy: 0.7721
Epoch 6/15
Epoch 6: 100% Accuracy: 0.7770
                                            51/51 [01:09<00:00, 1.36s/it, accuracy=0.777, loss=0.868]
Epoch 7/15
Epoch 7: 100% Accuracy: 0.7843
                                                | 51/51 [01:03<00:00, 1.24s/it, accuracy=0.784, loss=0.248]
Enoch 8/15
Epoch 8: 100%| Accuracy: 0.8113
                                                | 51/51 [01:01<00:00, 1.21s/it, accuracy=0.811, loss=0.524]
Epoch 9/15
| 51/51 [01:00<00:00, 1.18s/it, accuracy=0.826, loss=0.486]
Epoch 10/15
                                            | 51/51 [00:58<00:00, 1.15s/it, accuracy=0.828, loss=0.708]
Epoch 10 Loss: 0.3755 | Accuracy: 0.8284
Epoch 11/15
Epoch 11: 100% Accuracy: 0.8088
                                            | 51/51 [00:57<00:00, 1.12s/it, accuracy=0.809, loss=0.216]
Epoch 12/15
Epoch 12: 190%
                                               51/51 [01:02<00:00, 1.22s/it, accuracy=0.858, loss=0.227]
Epoch 12 Loss: 0.3239 | Accuracy: 0.8578
Epoch 13/15
                                                | 51/51 [01:05<00:00, 1.29s/it, accuracy=0.843, loss=1.02]
Epoch 13: 100% Accuracy: 0.8431
Epoch 14/15
Epoch 14: 100% Accuracy: 0.8529
                                               | 51/51 [01:00<00:00, 1.18s/it, accuracy=0.853, loss=0.223]
Epoch 15/15
Epoch 15: 100% Accuracy: 0.8456
                                                | 51/51 [01:06<00:00, 1.31s/it, accuracy=0.846, loss=0.388]
```

• Evaluation Metrics

Overall Accuracy: 72.55% Overall Precision: 61.08% Overall Recall: 60.42% Overall F1-Score: 60.70%

• Realtime Testing and Assessing Risk by Analysing Legal Possibilities:

Once you run the cells with an actual legal contract, the output will provide a summary of the document risk assessment. In the first step, open the document, extract the text and process it. Using a pre-trained BERT model, the processed text is input to classify the degree of risk the document poses, with outputs indicating the document is "Risky" or "Not Risky," based on the content. Based on probabilities representing the likelihood of each risk category, as predicted by the model.

The document is classified as: Not Risky Probability of being Risky: 0.0237 Probability of being Not Risky: 0.9763 No Risk Clauses Identified.

Legal BERT

After executing the Legal BERT code cell by cell you can see the following outputs

Legal-BERT model and tokenizer loaded.

• Filtering and Balancing Clauses Based on Yes/No Distribution

	No	Yes
Competitive Restriction Exception	434.0	76.0
Non-Compete	391.0	119.0
Exclusivity	330.0	180.0
No-Solicit Of Employees	451.0	59.0
Termination For Convenience	327.0	183.0
Rofr/Rofo/Rofn	425.0	85.0
Change Of Control	389.0	121.0
Anti-Assignment	136.0	374.0
Revenue/Profit Sharing	344.0	166.0
Minimum Commitment	345.0	165.0
Volume Restriction	428.0	82.0
Ip Ownership Assignment	386.0	124.0
License Grant	255.0	255.0
Non-Transferable License	372.0	138.0
Affiliate License-Licensee	451.0	59.0
Irrevocable Or Perpetual License	440.0	70.0
Post-Termination Services	328.0	182.0
Audit Rights	296.0	214.0
Uncapped Liability	399.0	111.0
Cap On Liability	235.0	275.0
Liquidated Damages	449.0	61.0
Warranty Duration	435.0	75.0
Insurance	343.0	167.0
Covenant Not To Sue	410.0	100.0

• Clause Distribution Analysis and Balancing for Classification

	No	Yes
Competitive Restriction Exception	434.0	76.0
Non-Compete	391.0	119.0
Exclusivity	330.0	180.0
No-Solicit Of Employees	451.0	59.0
Termination For Convenience	327.0	183.0
Rofr/Rofo/Rofn	425.0	85.0
Change Of Control	389.0	121.0
Anti-Assignment	136.0	374.0
Revenue/Profit Sharing	344.0	166.0
Minimum Commitment	345.0	165.0
Volume Restriction	428.0	82.0
Ip Ownership Assignment	386.0	124.0
License Grant	255.0	255.0
Non-Transferable License	372.0	138.0
Affiliate License-Licensee	451.0	59.0
Irrevocable Or Perpetual License	440.0	70.0
Post-Termination Services	328.0	182.0
Audit Rights	296.0	214.0
Uncapped Liability	399.0	111.0
Cap On Liability	235.0	275.0
Liquidated Damages	449.0	61.0
Warranty Duration	435.0	75.0
Insurance	343.0	167.0
Covenant Not To Sue	410.0	100.0

• Preparation and Split of Dataset for Specific Clause Classification

Training samples: 408 Testing samples: 102

4 Tokenize the training and testing data

Train Input IDs Shape: torch.Size([408, 20])
Test Input IDs Shape: torch.Size([102, 23])

5 Dataset and DataLoader Configuration for Model Training

Train Dataset Size: 408 Test Dataset Size: 102

6 Optimizer and Learning Rate Scheduler Setup for Training

Optimizer and scheduler set up with 260 total steps.

7 Model Training Loop

```
Epoch 1/10
Epoch 1: 100%
                                                           26/26 [00:45<00:00, 1.74s/it, accuracy=0.735, loss=0.247]
Epoch 1 Loss: 0.5617 | Accuracy: 0.7353
Epoch 2/10
                                                           26/26 [00:48<00:00, 1.88s/it, accuracy=0.767, loss=0.997]
Epoch 2 Loss: 0.5502 | Accuracy: 0.7672
Epoch 3/10
                                                           26/26 [00:45<00:00, 1.75s/it, accuracy=0.767, loss=0.483]
Epoch 3 Loss: 0.5451 | Accuracy: 0.7672
                                                           26/26 [00:45<00:00, 1.73s/it, accuracy=0.767, loss=0.583]
Epoch 4 Loss: 0.5369 | Accuracy: 0.7672
Epoch 5 Loss: 0.5462 | Accuracy: 0.7672
Epoch 6/10
                                                           26/26 [00:45<00:00, 1.77s/it, accuracy=0.767, loss=0.585]
                                                           26/26 [00:43<00:00, 1.69s/it, accuracy=0.767, loss=0.677]
Epoch 6 Loss: 0.5487 | Accuracy: 0.7672
Epoch 7: 100% | Epoch 7 Loss: 0.5238 | Accuracy: 0.7672 | Epoch 8/10
                                                          26/26 [00:48<00:00, 1.88s/it, accuracy=0.767, loss=0.298]
Epoch 8: 100%| Epoch 8 Loss: 0.5356 | Accuracy: 0.7672 Epoch 9/10
                                                          26/26 [00:51<00:00, 1.99s/it, accuracy=0.767, loss=0.709]
Epoch 9: 100%
                                                           26/26 [00:51<00:00, 1.98s/it, accuracy=0.767, loss=0.736]
Epoch 9 Loss: 0.5241 | Accuracy: 0.7672
Epoch 10/10
Epoch 10: 100% Accuracy: 0.7672
                                                           26/26 [00:46<00:00, 1.79s/it, accuracy=0.767, loss=0.513]
```

8 Evaluation Metrics

Accuracy: 76.47% Overall Metrics: Precision: 0.58 Recall: 0.76 F1-Score: 0.66

• Realtime testing

The document is classified as: Not Risky

Probability of being Risky: 0.2713

Probability of being Not Risky: 0.7287

No Risk Clauses Identified.

4. Configuration for Anomaly Detection

• Structure of dataset

<pre>df = pd.read_csv(path)</pre>								
df								
Un	named: 0	clause_text	clause_type	totalwords	totalletters			
0	0	Make any Investments, except:	investments	4.0	30.0			
1	1	No more than 45% of the "value" (as defined i	investments	76.0	460.0			
2	2	Make or hold any Investments, except:	investments	6.0	38.0			
3	3	The SubAdviser is hereby authorized and direc	investments	228.0	1474.0			
4	4	Make any advance, loan, extension of credit (investments	52.0	329.0			
21182	9105	The Placement Agent (i) will keep the Confiden	Confidentiality	371.0	2503.0			

282.0

376.0

198.0

309.0

1811.0

2339.0

1214.0

2121.0

• Average Total Letters by Clause Type

9106 Except as otherwise provided by Legal Requirem... Confidentiality

9109 The Executive recognizes that any knowledge an... Confidentiality

Each Lender agrees to keep confidential any wr... Confidentiality

Executive agrees that he will not at any time,... Confidentiality

21183

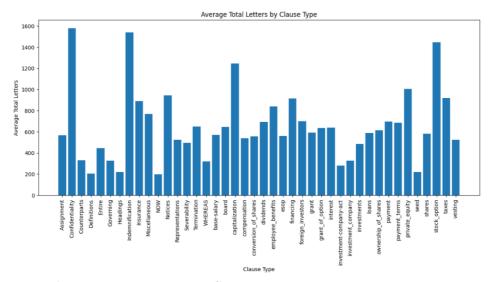
21184

21185

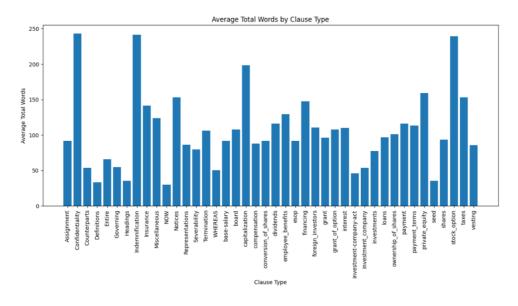
21186

9107

9108



• Average Total Words by Clause Type



• Displaying Average Words and Letters

Average Total Words by	Clause Tunes
clause type	avg totalwords
Assignment	91.574603
_	243.016667
Confidentiality	243.016667 53.450794
Counterparts Definitions	
	33.042697
Entire	65.931343
Governing	54.718182
Headings	35.509302
Indemnification	241.408108
Insurance	141.670213
Miscellaneous	123.886792
NOW	29.661111
Notices	153.018750
Representations	86.296721
Severability	79.424138
Termination	106.103390
WHEREAS	50.163014
base-salary	91.466337
board	107.959184
capitalization	198.544086
compensation	88.007049
conversion_of_shares	91.516667
dividends	115.949861
employee_benefits	129.413333
esop	91.963801
financing	147.294118
foreign_investors	110.571429
grant	96.322727
grant_of_option	107.988889
interest	110.034653
investment-company-act	45.702000
investment_company	53.880000
investments	77.323647
loans	96.972648
ownership_of_shares	100.859000
payment	116.146146

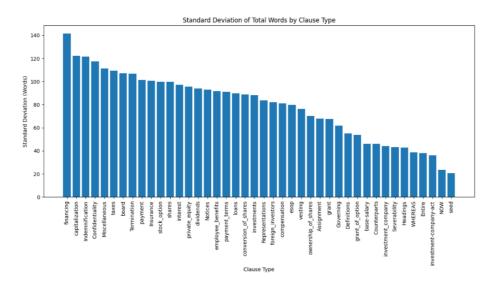
Average Total Letters b	ov Clause Type:
	avg_totalletters
Assignment	567.300000
Confidentiality	1578.727778
Counterparts	329.131746
Definitions	206.339326
Entire	445.050746
Governing	327.481818
Headings	220.063953
Indemnification	1541.251351
Insurance	889.378723
Miscellaneous	768.550943
NOW	198.133333
Notices	943.506250
Representations	522.903279
Severability	494.987931
Termination	649.476271
WHEREAS	318.001370
base-salary	570.022772
board	646.910204
capitalization	1245.992473
compensation	538.065458
conversion_of_shares	555.250000
dividends	693.543175
employee_benefits	840.320000
esop	560.918552
financing	914.317647
foreign_investors	698.500000
grant	592.200000
grant_of_option	636.811111
interest	640.685149
investment-company-act	279.369000
investment_company	327.270000
investments	484.158317
loans	588.725383
ownership_of_shares	615.420000
payment	697.661662

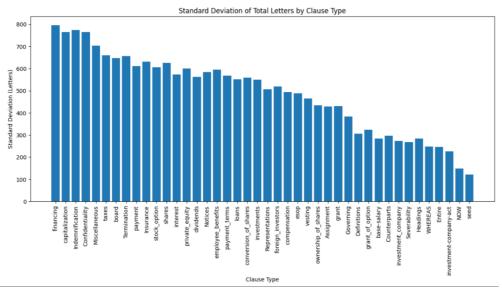
• Sorting and Displaying Variability

Least Variable Clause Types (by std_totalwords):

clause_type	std_totalwords	std_totalletters
seed	20.481124	121.313456
NOW	23.411024	148.382075
investment-company-act	36.053919	225.346937
Entire	38.045069	246.286374
WHEREAS	38.456959	248.632857

• Standard Deviations Plot





• Data Inspection

```
Columns in Dataset:
Index(['clause_text', 'clause_type', 'totalwords', 'totalletters'], dtype='object')
Unique Values in 'clause_type':
['investments' 'capitalization' 'private_equity' 'interest' 'vesting'
    'employee_benefits' 'esop' 'ownership_of_shares' 'foreign_investors'
    'loans' 'stock_option' 'investment_company' 'seed' 'board' 'financing'
    'grant_of_option' 'payment_terms' 'taxes' 'payment' 'compensation'
    'base-salary' 'investment-company-act' 'dividends' 'shares' 'grant'
    'conversion_of_shares' 'WHEREAS' 'NOW' 'Notices' 'Governing'
    'Counterparts' 'Severability' 'Miscellaneous' 'Definitions' 'Entire'
    'Termination' 'Indemnification' 'Headings' 'Representations' 'Assignment'
    'Insurance' 'Confidentiality']
```

No 'risk_level' column detected. Consider adding labels for supervised learning.

• Data Cleaning and Outlier Removal

Shape of the streamlined DataFrame: (19501, 3)

• Feature Engineering: TF-IDF and Scaling

Shape of combined features: (19501, 502)

• Anomaly Detection with Isolation Forest

```
Anomaly Detection Results (Score Counts):
anomaly_score
1 18526
-1 975
Name: count, dtype: int64
```

• Analysis and Display of Detected Anomalies

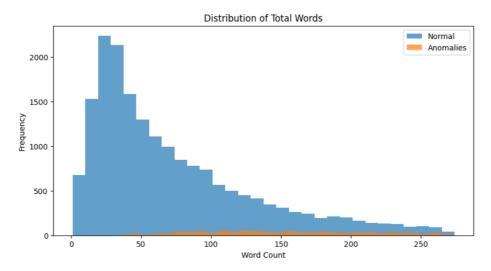
```
Statistics of Anomalies:
      totalwords totalletters
count 975.000000
                  975.000000
mean 153.433846
                   946.046154
       59.189594
                  366.419440
std
      33.000000
min
                  179.000000
25%
      107.000000
                   647.000000
50%
     150.000000
                  919.000000
75%
      201.000000
                  1235.000000
     273.000000 1680.000000
max
Sample Anomalous Clauses:
                                        clause_text totalwords
     All or a portion of amounts in the Certificat...
    (i) Other than in accordance with the investm...
92
                                                         180.0
104 Subject to the 1940 Act, the direction of Adv...
                                                         118.0
115 Cadence has furnished to Trustmark a complete...
                                                         124.0
120 Except for Permitted Investments (including i...
                                                        151.0
    totalletters
12
          1577.0
92
          1087.0
104
           813.0
115
           795.0
          1058.0
120
```

9 Statistics for Normal data

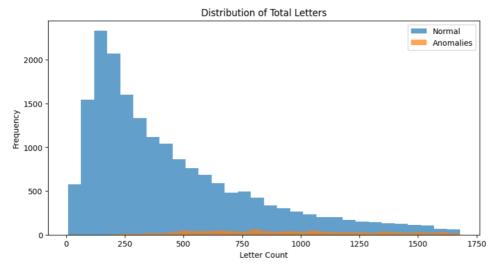
Statistics of Normal Data:

	totalwords	totalletters
count	18526.000000	18526.000000
mean	72.863273	447.965508
std	57.973151	355.778009
min	1.000000	7.000000
25%	29.000000	178.000000
50%	54.000000	333.000000
75%	101.000000	619.000000
max	274.000000	1680.000000

• Distributions of Totalwords



• Distributions of Total Letters



References

Python: https://www.python.org

Dataset 1: CUAD Dataset https://www.atticusprojectai.org/cuad **Dataset 2:** legal clauses dataset link:

 $\underline{https://www.kaggle.com/datasets/mohammedalrashidan/contracts-}\\ \underline{clauses-datasets}$