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CHAIR OF DISTRIBUTED INFORMATION SYSTEMS

Argument Quality Assessment Over Textual Data

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1 Motivation

2[nd] *Contribution:* Investigate model robustness [Alh+22a]. → **Argument Mining**

1[st] *Contribution:* design a model to predict the **Strength** AQ dimension using the FinArgQuality corpus. → **Argument Quality Assessment**

Earnings Conference Call

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Argument Mining

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Argumentative Structure

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Argument Quality Assessment

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Argumentation Quality

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Prediction

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Analyst Post-Call Recommendation

Figure : The steps for the prediction of analyst post-call recommendation.

2 Introduction

Argument Definition

An argument consists of one claim (i.e., conclusion) supported or attacked by at least one premise (i.e., evidence) [DS19].

3

Argument Quality

1st Contribution

Submitted paper: Is it a Reliable Answer? Quality Assessment of Managers' Arguments in Earnings Conference Calls

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Argument Mining

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Prediction

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Analyst Post-Call Recommendation

Argument Quality Assessment

- Rate arguments according to their quality.
- Quality is determined by the **arguments' components** and the **relation** between them.

- Level of Granularity

Argument unit level [SKW21].

Argument level [Gre+20; SG17b].

Argumentation level [Wal+06].

Debate level [Coh+21; Eem+04].

- Approaches

Pair-wise approach [SKW21].

Point-wise approach [Wac+17b; Gre+20; SG17b].

Existing Corpora

Table : Datasets for argument quality.

Dataset	Source	Size	Approach	Quality dimensions
SwanRank [SEW15]	Internet Argument	5.3K arguments	Point-wise	Context Inference
UKPConvArgRank [HG16]	Online debate forum	16K pairs of arguments	Pair-wise	Convincingness
dagstuhl-15512- argquality [Wac+17b]	Online debate forum	320 arguments	Point-wise	15 dimensions [Wac+17b]
IBM Debater® - IBMArgQ-Rank-30kArgs [Gre+20]	Arguments from crowds	30K arguments	Point-wise	15 dimensions [Wac+17b]

FinArgQuality Corpus

- A point-wise annotated corpus, in the **argument** and **argument unit** levels of granularity.
- 5 Quality dimensions:
  - **Strong**, Persuasive, Specific, Objective, TemporalHistory.
- 2184 arguments
  - 2184 claims
  - 4899 Premises

Computational Argument Quality Assessment

Table : Argument Quality Assessment.

Paper	Argument Quality Assessment Dimension
[Gre+20]	Overall quality
[PN15]	Strength
[HG16]	Convincingness
[WSA17]	Relevance
[PN13]	Clarity
[Lau+20]	Cogency, Reasonableness, Effectiveness

Challenges

- **Main Goal:** Design a model to assess argument **Strength** based on FinArgQuality corpus level of granularity.

- **Challenge 1:** Dataset is imbalanced.
- **Challenge 2:** How to incorporate categorical features to improve the prediction of the strength dimension.

Proposed Approach

- Predict the strength score of arguments.
- Multi-class classification problem.

- Bert model: the **state-of-the-art** in the argument quality assessment [Gre+20; GAW21; SKW21].
- XLNet outperforms Bert in 20 benchmark tasks [YAN+19].

- Use the iterative stratified sampling over 10-fold cross-validation [STV11; SK17].

Model	Execution time (3 epochs)	Macro-F1 score	
		Mean	SEM
Bert	50 mins	.48	+- .01
XLNet	150 mins	**.49**	**+- .00**

- No significant improvement.
- The running time of XLNet.
- → Select the **Bert** model.

Baseline

Bert Model

Proposed Approach

- Input = **[cl_text]** claim **[/cl_text] [pr_text]** premise_1 **[/pr_text]** … Premise_n **[/pr_text]**
- Output = 0, 1 or 2

Results & Discussion: Bert with special separator token

Table : Evaluation of the different examined models, on ***FinArgQuality****, where SEM stands for standard error of the mean*

Model	**Macro-F1 score**		**Accuracy**	
	Mean	**SEM**	**Mean**	**SEM**
Bert (Baseline)	.48	+- .01	.74	+- .01
Bert, special separator token	**.50**	+- .00	**.77**	**+- .01**

Proposed Approach

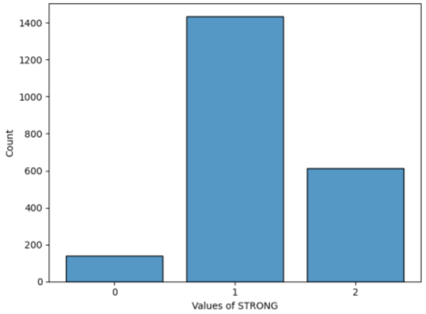
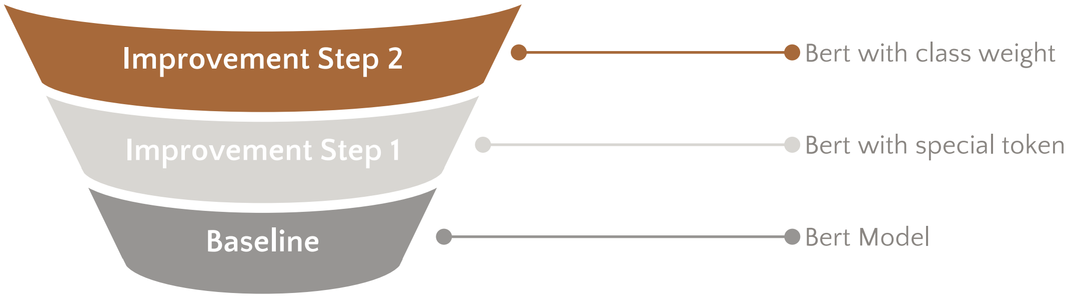


Figure: Distribution of the Strong dimension

Imbalanced classes → Macro-F1 score [LLS09].



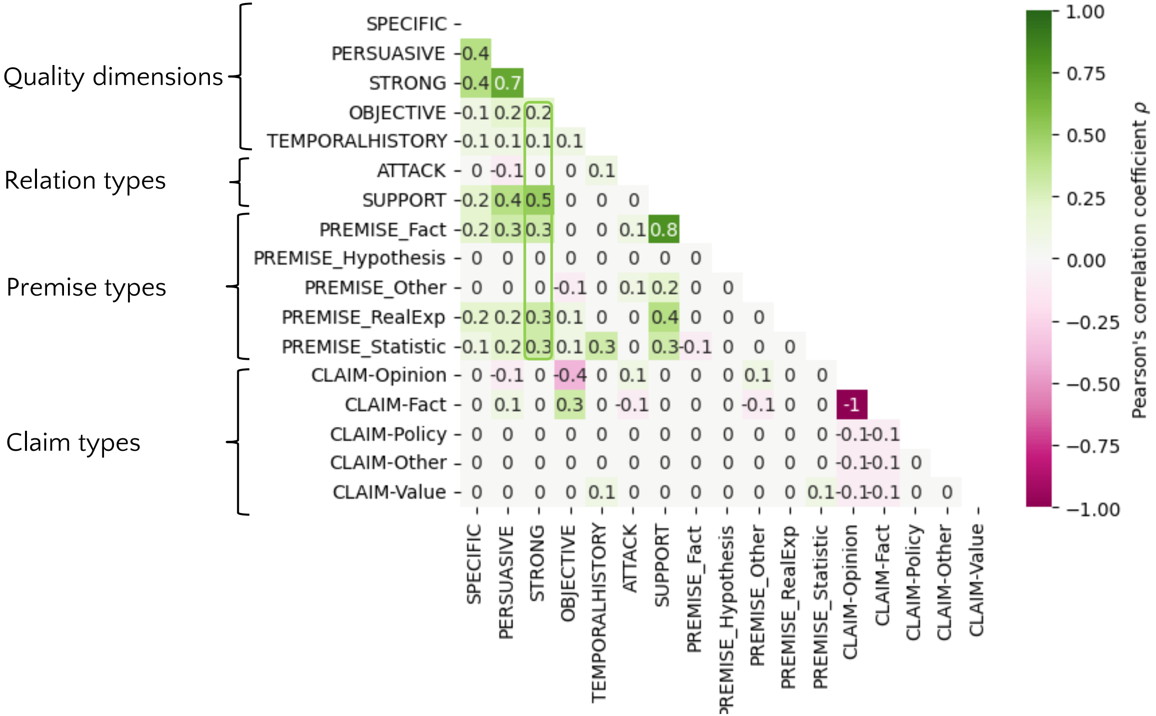
Results & Discussion: Bert with class weight

Table : Results of the macro-F1 score on the different class weights.

Class 0	Class 1	Class 2	macro-F1 score
5	1	1	0.46
6	1	1	0.50
7	1	1	0.53
9	1	1	0.52
10	1	1	0.48
11	1	1	0.48
5	1	2	0.50
6	1	2	0.48
7	**1**	**2**	**0.56**
8	**1**	**2**	**0.55**
9	1	2	0.54
10	1	2	0.48
11	1	2	0.54

- $p=0.15$ (> 0.05) for the weights [7,1,2]
- $p=0.01$ (< 0.05) for the weights [8,1,2]

→ **[8,1,2]**



Strength dimension:
An argument's strength is determined by the number and types of premises that support its claim.

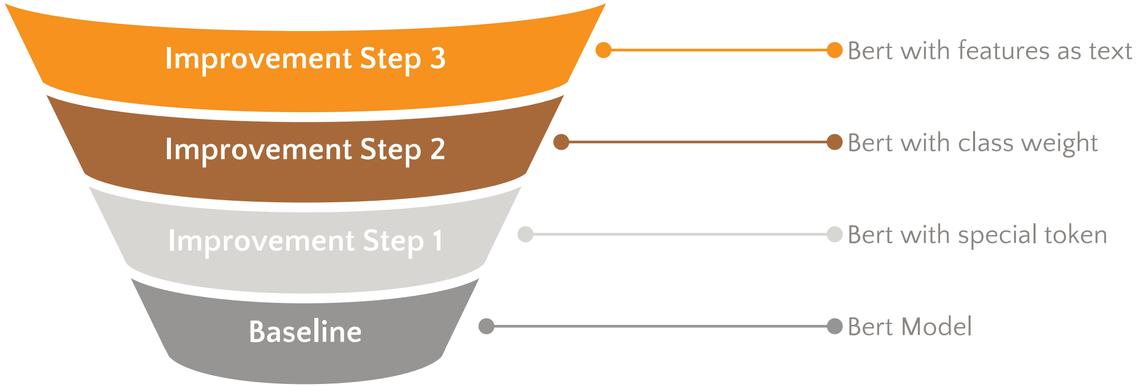
Figure: Correlation between argument quality dimensions

Why Bert with Features?

- For small datasets, when more features are incorporated into a model, simple models may **outperform** complex ones [PM20].
- For the Stance Detection task, Prakash and Madabushi highlight the advantage of including Count-Based features in the pre-trained models [PM20].

Proposed Approach

Input =
[cl_text] *It's a very rapidly expanding country.* [/cl_text]
[cl_type] *Claim-Opinion* [/cl_type]
[r_type] SUPPORT [/r_type]
[pr_text] *Constant currency growth was 48%.*[/pr_text]
[pr_type] *Premise-Statistic* [/pr_type]
Output = 1



Results & Discussion: Bert with features as text

Table: The results of Bert model with categorical features as text, where SEM stands for standard error of the mean

Feature Format	Included features			Metric	
	Claim type	**Premise type**	Relation type	Macro-F1	
				Mean	SEM
Baseline	x	x	x	.55	+- .02
Feature as test	✓	x	x	.50	+- .04
	x	**✓**	**x**	**.56**	**+- .01**
	x	x	✓	.54	+- .01
	✓	✓	x	.55	+- .02
	x	✓	✓	.54	+- .01
	✓	x	✓	.49	+- .04
	✓	✓	✓	.53	+- .02

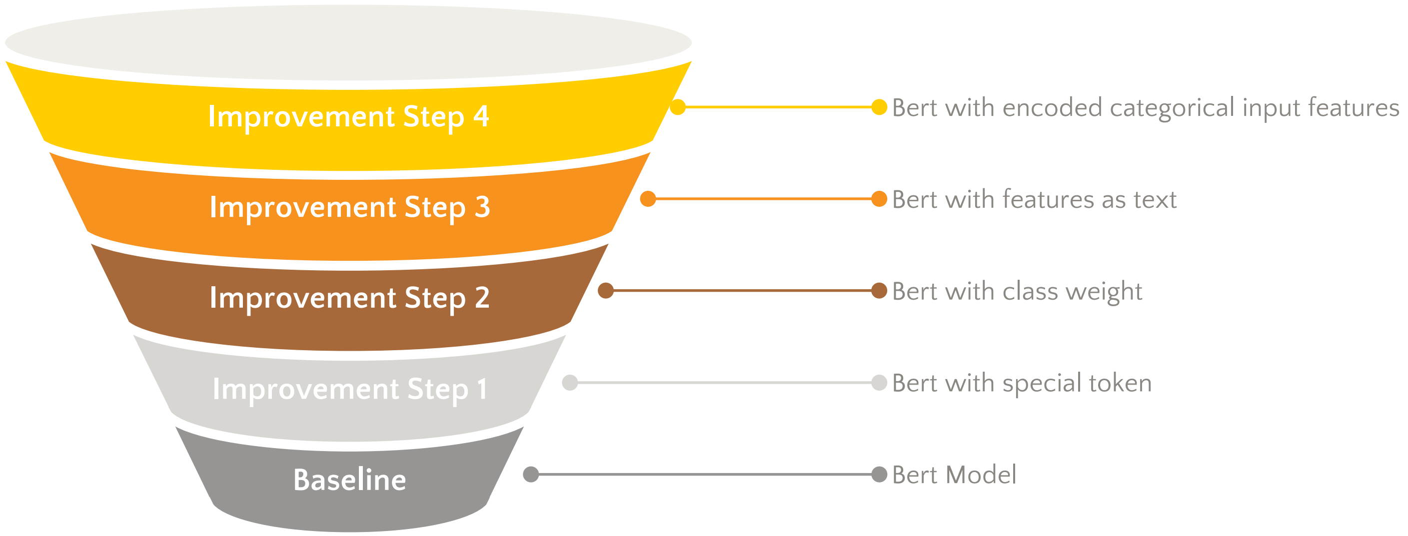
- Shapley values [SHA53].

Claim type: -3%

Relation type: -1.5%

Premise type: +2.5%

Proposed Approach



[CLS] is the special symbol for classification output [Dev+18].

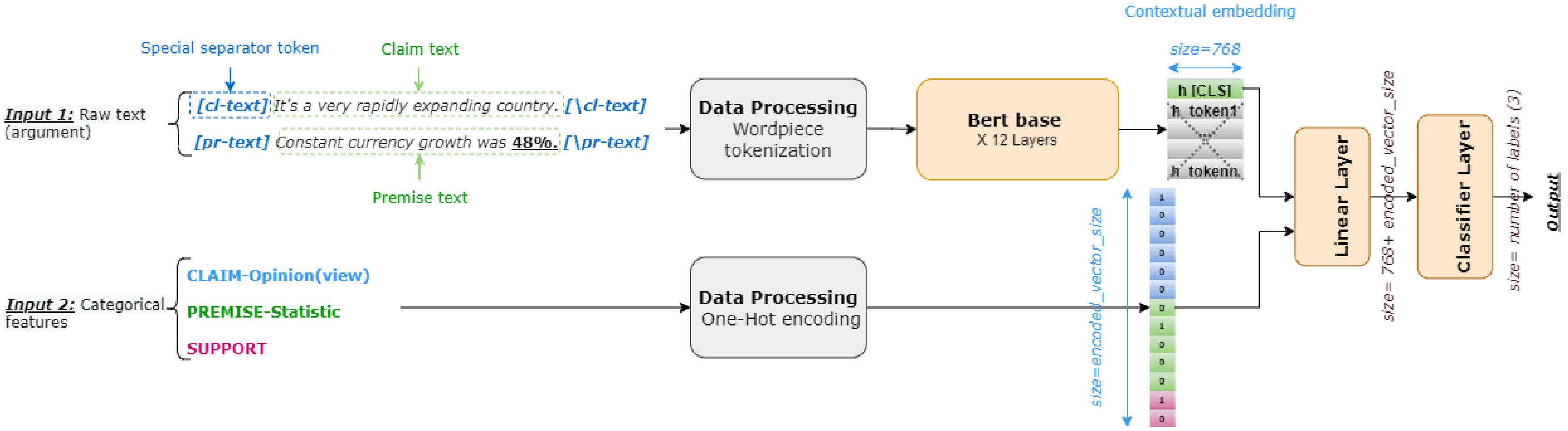


Figure: Model architecture for Bert with encoded categorical input features

Results & Discussion: Bert with Encoded Categorical Input Features

Table: The results of Bert model with categorical features as text, where SEM stands for standard error of the mean

Feature Format	Included features			Metric	
	Claim type	**Premise type**	Relation type	Macro-F1	
				Mean	SEM
Baseline	x	x	x	.55	+- .02
One-Hot Encoding	✓	x	x	.57	+- .01
	x	**✓**	**x**	**.59**	**+- .02**
	x	x	✓	.57	+- .01
	✓	✓	x	.58	+- .01
	x	✓	✓	.57	+- .01
	✓	x	✓	.57	+- .01
	✓	✓	✓	.55	+- .01

- Shapley values [SHA53].

Claim type: -0.17%

Relation type: -0.67%

Premise type: +0.83%

Results & Discussion

Table : Evaluation of the different examined models, on ***FinArgQuality****, where SEM stands for standard error of the mean*

Model	**Macro-F1 score**		**Accuracy**	
	Mean	**SEM**	**Mean**	**SEM**
Bert (Baseline)	.48	+- .01	.74	+- .01
Bert, special separator token	.50	+- .00	**.77**	**+- .01**
Bert, class weight	.55	+- .02	.67	+- .02
Bert, features as text	.56	+- .01	.71	+- .01
Bert, One-Hot Encoding	**.59**	**+- .02**	.71	+- .01

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4 Model Robustness

2nd Contribution

Alhamzeh, Alaa, Előd Egyed-Zsigmond, Dorra El Mekki, Abderrazzak El Khayari, Jelena Mitrović, Lionel Brunie, and Harald Kosch. "Empirical Study of the Model Generalization for Argument Mining in Cross-Domain and Cross-Topic Settings." In Transactions on Large-Scale Data-and Knowledge-Centered Systems LII, pp. 103-126. **Springer**, Berlin, Heidelberg, 2022.

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Challenges

- The lack of labelled data.
- The domain dependency performance of the existing models.

→ Investigate model robustness.

Research Goals

Baseline

Ensemble learning approach.

Task: Argument identification

Datasets: Student Essays and Web Discourse.

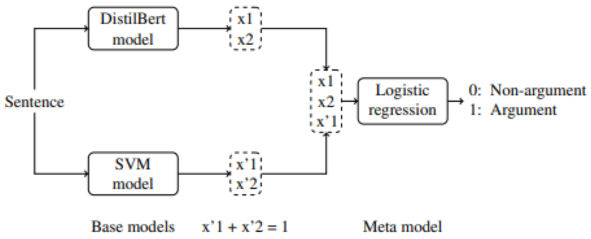

Figure: Stacked Model Architecture [Alh+21].

Research Goals

RG1: Extend the ensemble learning approach.

Tasks: argument identification and argument unit classification.

Datasets: Student Essays, Web Discourse and IBM corpus.

RG2: Conduct an empirical study of the model generalization in cross-domain and cross-topic settings.

RG3: Study the trade-off between the number of topics #T and the number of samples per topic #S/T to enhance the model generalization.

Model Generalization

	Paper	Task(s)	Algorithm(s)	Dataset(s)	Approach	Comments
1	Schiller et al. [SDG21]	Stance detection	Bert	10 heterogeneous datasets	SDL vs. MDL	-Different task -Same approach
2	Ajjour et al. [Ajj+17]	argument unit segmentation	NN model	3 corpora	Cross Domain	-Features on the token level. -Our features on the sentence level.
3	Bouslama et al. [BAA19].	extract the argument from the web and classify its components	CNN SVM Naïve Bayes	3 corpora	Cross Domain	-Different task -Same approach
4	Stab et al. [SMG18].	Argument identification with respect to the topic	LSTM	25,000 instances over eight topics	Cross Topic	-Different setup -We investigate the effect of diversity sampling.

Proposed Approach

- Extend the ensemble learning stacking approach proposed in [Alh+21] on the **argument unit classification (premise/claim)** and train it on the **IBM corpus** [Aha+14].
- Investigate the model robustness over **unseen data**.

Experimental Setup

Task	**Algorithms**	**Datasets**	**Epochs**	**Optimizer**	**Loss**	**Seeds**	**Train-test**
Argument identification	SVM DistilBert (Stacking approach)	Student Essays [SG14a] Web Discourse [HG17]	3	AdamW optimizer	Cross-Entropy	5	5-cross validation
Argument unit classification	SVM DistilBert (Stacking approach)	Student Essays [SG14a] Web Discourse [HG17] **IBM [Aha+14]**	3	AdamW optimizer	Cross-Entropy	5	5-cross validation

Corpora description

Table: Class distributions for all used datasets.

	Student Essays [SG14a]		**Web Discourse [HG17]**		**IBM [Aha+14]**		**Total**
	Count	**[%]**	**Count**	**[%]**	**Count**	**[%]**	
Argument	**5459**	**60**	1025	11	2683	29	9167
Non-Argument	**1358**	**77**	411	23	0	0	1769
Premise	**3510**	**62**	830	15	1291	23	5631
Claim	**1949**	**55**	195	6	1392	39	3536
Topic	**372**	**91**	6	1	33	8	411

Approach: SDL vs MDL

- For the SDL, a single dataset is used to train and test the model.
- For the MDL, we train on all datasets and test on the test set of one dataset.

Results & Discussion: SDL vs MDL

Table: SDL vs. MDL argument identification and argument unit classification using the stacked model.

		Argument identification		**Argument unit classification**	
		Macro-F1 score		**Macro-F1 score**	
		Mean	**Std**	**Mean**	**Std**
SDL	SE	**.864**	+- .004	**.808**	+- .004
	WD	**.715**	+- .020	**.803**	+- .016
	IBM	-	-	**.987**	+- .002
MDL	SE	.776	+- .007	.693	+- .141
	WD	.661	+- .024	.670	+- .035
	IBM	-	-	.894	+- .008

Discussion

- SDL gives a better performance, while MDL can improve the model robustness and stability over unseen data.
- Detecting argumentative text proved to be an intrinsically more generalized task than determining premises and claims.

Approach: Cross Domain

- Testing on completely unseen datasets.
- The model is trained on n – 1 corpora and tested on the remaining one.

Results & Discussion: Cross Domain

Table: Evaluation of the cross-domain argument identification task.

Training	Testing	Model	Macro-F1 score	
			Mean	**Std**
SE	**WD**	Stacked model	.436	+- .009
		DistilBert	**.571**	+- .005
		[Al +16]	.524	-
WD	**SE**	Stacked model	**.599**	+- .009
		DistilBert	.580	+- .015
		[Al +16]	.128	

Table: Evaluation of the cross-domain argument identification task.

Training	Testing	Model	Macro-F1 score	
			Mean	**Std**
SE,WD	**IBM**	Stacked model	**.554**	+- .079
		DistilBert	.469	+- .023
SE, IBM	**WD**	Stacked model	.455	+- .196
		DistilBert	**.602**	+- .012
WD, IBM	**SE**	Stacked model	**.526**	+- .060
		DistilBert	.366	+- .057

Discussion

- A drop in performance of the stacked model compared to in-domain settings (0.784 for argument identification and 0.869 for argument unit classification).
- For limited dataset, incorporating the features might play a crucial role to achieve reliable results.

Experimental Setup : Cross Topic

RQ: Given a fixed size of data, would it be better to include more topics with fewer sentences per topic or fewer topics with more sentences per topic?

$$\boldsymbol{N = \#T.\#S/T}$$

- $\boldsymbol{\#T}$ is the number of topics (variable).
- $\boldsymbol{\#S/T}$ is the number of sentences per topic (variable).
- **N** is the fixed size of data.

Fix N in a way that we can have multiple pairs of (#S/T, #T) satisfying the Equation, this implies that a higher #T leads to a lower #S/T.

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Results: Cross Topic

Table: Cross-topic experiments for argument identification task.

#S/T	#T	Model	Macro-F1 score	
			Mean	Std
4	300	Stacked model	**.806**	+- .029
		DistilBert	.566	+- .095
6	200	Stacked model	.766	+- .017
		DistilBert	.487	+- .056
24	50	Stacked model	.660	+- .038
		DistilBert	.439	+- .012

Table: Cross-topic experiments for argument unit classification task.

#S/T	#T	Model	Macro-F1 score	
			Mean	Std
4	300	Stacked model	.804	+- .036
		DistilBert	.748	+- .031
6	200	Stacked model	.817	+- .020
		DistilBert	.779	+- .018
24	50	Stacked model	**.846**	+- .070
		DistilBert	.828	+- .091

#S/T: *number of Sentences/Topic*, **#T**: *number of Topics, Std: standard deviation*

Discussion: Cross Topic

- The effect of diversity sampling

Observation:

For argument identification: higher #T (train) → higher macro-F1

For argument unit classification: higher #T (train) → lower macro-F1

Discussion:

The argument structure may vary depending on the topic (law vs. finance-related topics).

The argument unit classification, separating premise from claim is determined by the grammatical structure of sentences, which is independent of the employed vocabulary or the topic (claim vs. premise keywords).

5 Conclusion

Conclusion: Argument Quality Assessment

- A linear relation between the **Specific**, **Persuasive**, and **Strong** quality dimensions proved by the highest inter-correlation.
- We identify a positive correlation between the **Strong** quality dimension and the **premise/relation types**.

- The **premise type** contributes positively to the prediction of the **Strength** quality dimension.
- The proposed model architecture incorporating encoded categorical features (premise type) improves the macro-F1 score by 11% over the Bert baseline model.
- The model can be adjusted to predict the **Specific** and **Persuasive** quality dimensions.

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Conclusion: Model Robustness

- We extend the stacking approach from the argument identification to the argument unit classification task and we enlarge the size of the training set.
- We investigate the model robustness over unseen data: **SDL vs. MDL**, **Cross-domain** settings, **Cross-topic** settings.

- Despite the drop in performance compared to in-domain settings, the model is still able to generalize.
- Detecting argumentative text (**argument identification**) proved to be an intrinsically more generalized task than determining premises and claims (**argument unit classification**).
- For limited dataset, incorporating the features might play a crucial role to achieve reliable results.

Future Outlook

- Feature analysis study for the argument quality assessment model.
- Data valuation, removing outliers.
- A Leave-one-company-out experiment to study the similarities across data sources.
- End-to-end pipeline.

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Thank you for your attention!

Any questions ?