Transfer Learning and Textual Analysis of Accounting Disclosures:

Applying Big Data Methods to Small(er) Data Sets

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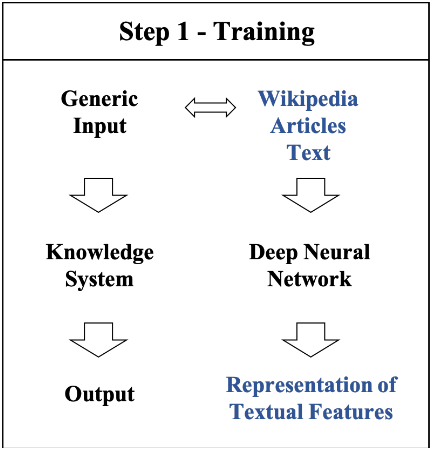
- Machine Transfer Learning represents a **powerful** yet **accessible** methodological tool **to understand language**, thus a dimension of human behavior, in the business context
- **Textual analysis** seems to have reached a **plateau**: current approaches largely employ **dictionary-based** and **statistical techniques** that are **unable** to account for **context** within corporate communications

Machine Transfer Learning

- Consists in **transferring** deep neural **networks' knowledge** (i.e., features representation), acquired through generic inputs, **to domain-specific tasks** (i.e., classification, regression, dimensionality reduction)

Machine Transfer Learning



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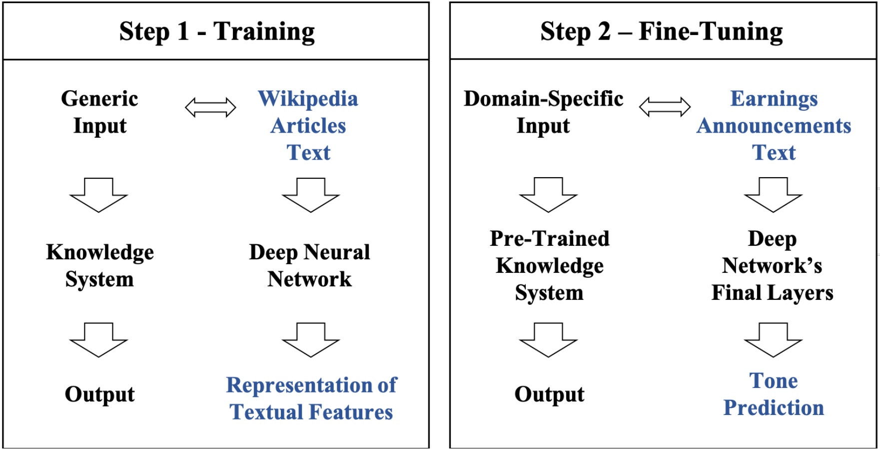

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- Low resource intensiveness is achieved through **fine-tuning only the last few layers** of the network using **small-scale inputs**
- An **applied researcher** can exploit a **powerful** pre-trained model for **the modest cost** of task-specific fine-tuning

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- *BERT*'s recipe combines **bi-directionality** and **transformers** to model **non-sequential, long-range semantic associations**

Bi-directionality

$\texttt{We use }\textcolor{red}{\texttt{[MASK]}}\texttt{ }\overbrace{\texttt{to portray business performance}}^{\textit{context}}$

$\underbrace{\texttt{What should I expect when studying}}_{\textit{context}}\texttt{ }\textcolor{red}{\texttt{[MASK]}}\texttt{?}$

Accounting is predicted based on a richer left-to-right and right-to-left characterization

Transformers

Accountants

Serve

A

Crucial

Role

In

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Because

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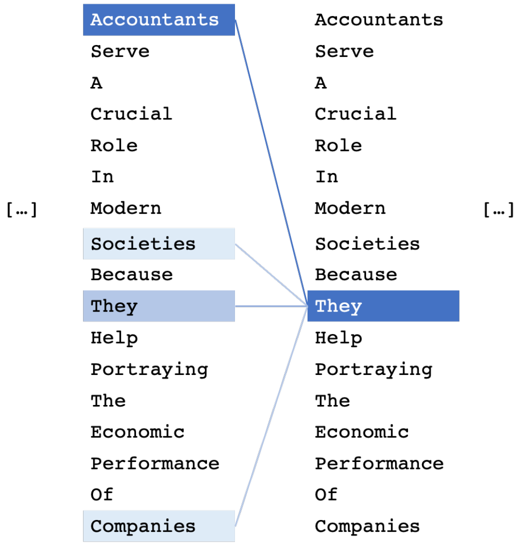
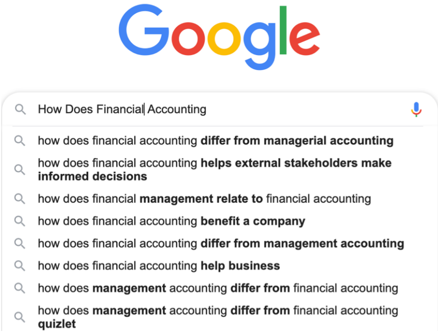
Transformers



A Real World Application



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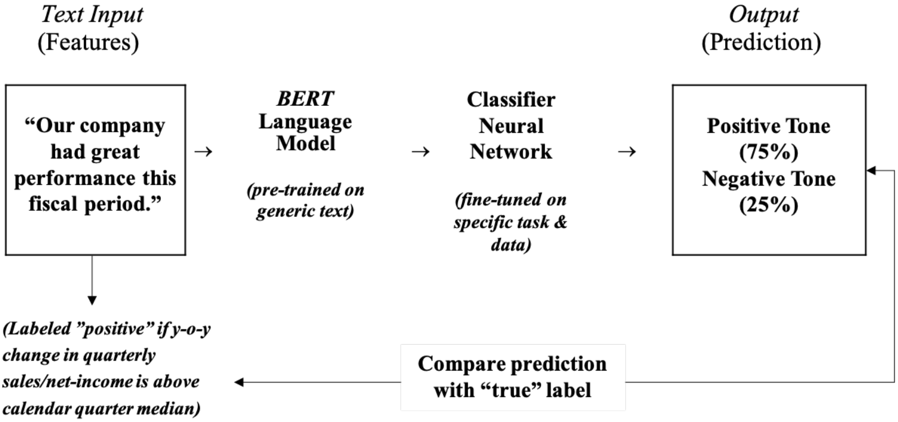
- **Recent works** have focused on **the tone** of earnings announcements or 10-K filings
- **Tone** is a multi-dimensional, **context-specific** construct that can be hardly characterized through **word-based approaches**

The Accounting Task



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    1. to **maximize** the **signal-to-noise** ratio
    2. to **show** the **power** of Transfer Learning using a **small dataset** of earnings announcements
    3. due to **technical reasons** related to transformers and attention

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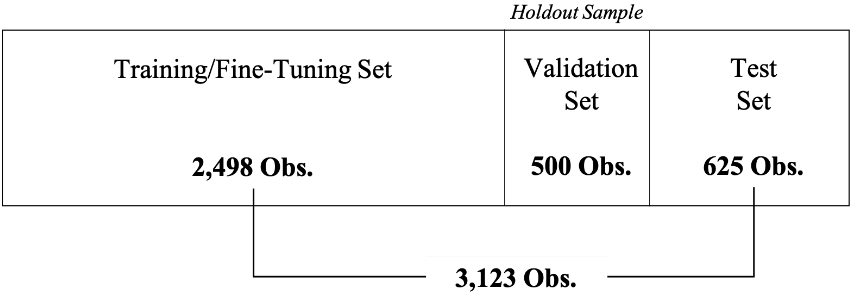
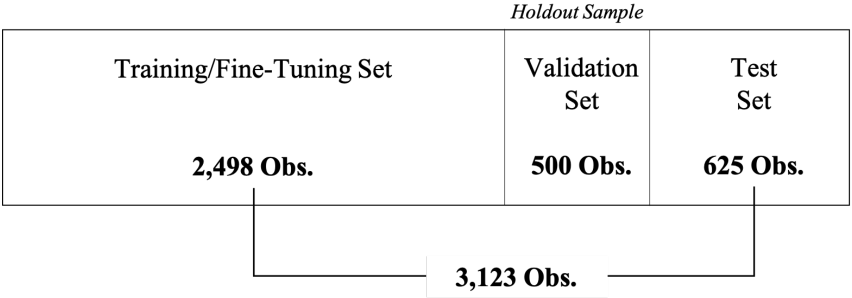
- We then perform **"masking" tests** to gather insights into **BERT's functioning**

The Sample


Holdout Sample
Training/Fine-Tuning Set
2,498 Obs.
Validation Set
500 Obs.
Test Set
625 Obs.
3,123 Obs.

The Sample



Labels (i.e., positive and negative) are almost **balanced** across sample sets

Model's Validation

- We select a **random sample of 500 observations** to identify the proper models' **hyper-parameters**

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- We select a **random sample of 500 observations** to identify the proper models' **hyper-parameters**
- The validated *BERT* model:
  1. *BERT* Base Uncased with 12 layers and 768 hidden states
  2. 2e-5 learning rate
  3. 3 training epochs

Main Results

BERT Model Selection and Cross-Validation Results on the Sample of Selected Business Wire Q1 Earnings Announcements

	Training Obs. (n= 2,498) Positive Labels	Training Obs. (n= 2,498) Negative Labels	Test Obs. (n=625) Positive Labels	Test Obs. (n=625) Negative Labels	AUC	Evaluation Accuracy	F1 Score
Panel A: 10-sentence Documents							
Average Test Results on 10-sentence Documents using Ten-fold Cross-Validation	**1,380**	**1,118**	**343**	**282**	**0.76**	**0.77**	**0.75**
Panel B: 15-sentence Documents							
Average Test Results on 15-sentence Documents using Ten-fold Cross-Validation	**1,380**	**1,118**	**343**	**282**	**0.78**	**0.79**	**0.78**
Panel C: Benchmarking Models							
Loughran-McDonald Dictionary Classification	**NA**	**NA**	**343**	**282**	**NA**	**0.64**	**0.64**
Naïve Bayes Sentiment Classifier (TextBlob)	**NA**	**NA**	**343**	**282**	**NA**	**0.53**	**0.68**
Random (Dummy) Classifier	**1,380**	**1,118**	**343**	**282**	**0.49**	**0.50**	**0.54**

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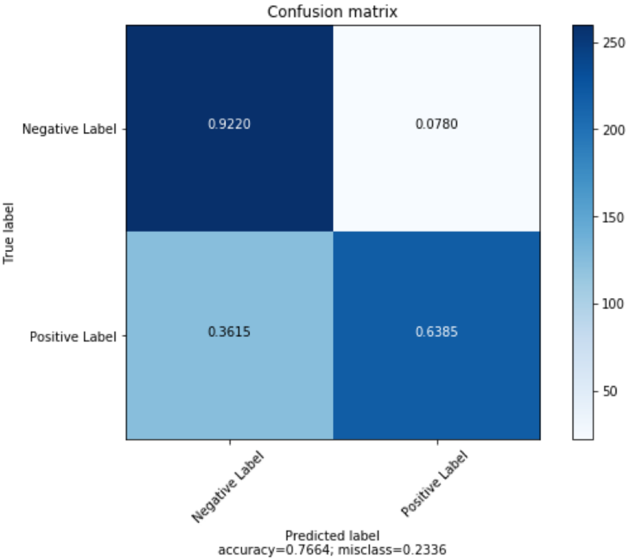
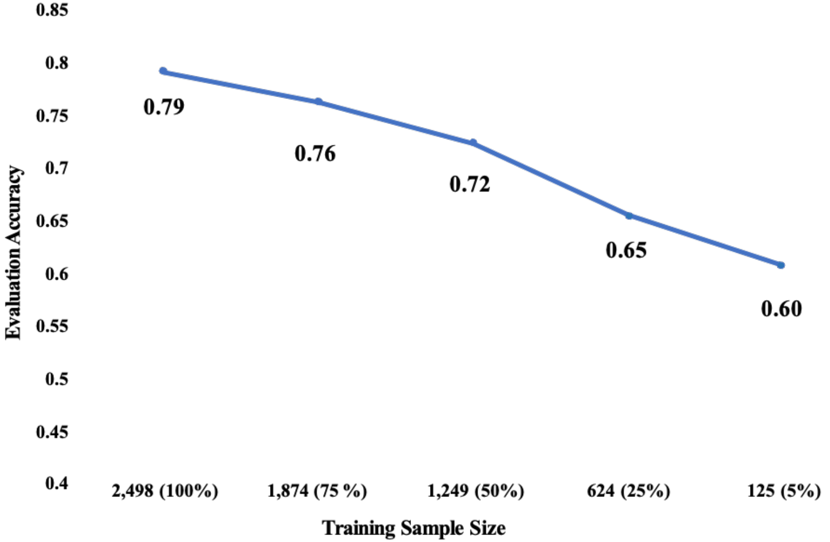
BERT Confusion Matrix



Evaluation Accuracy Across Distinct Sample Sizes



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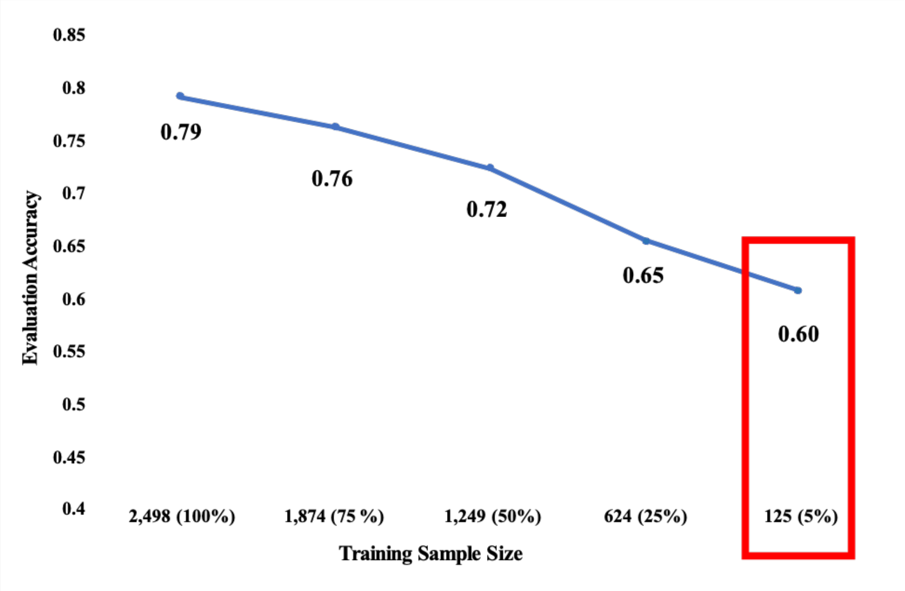
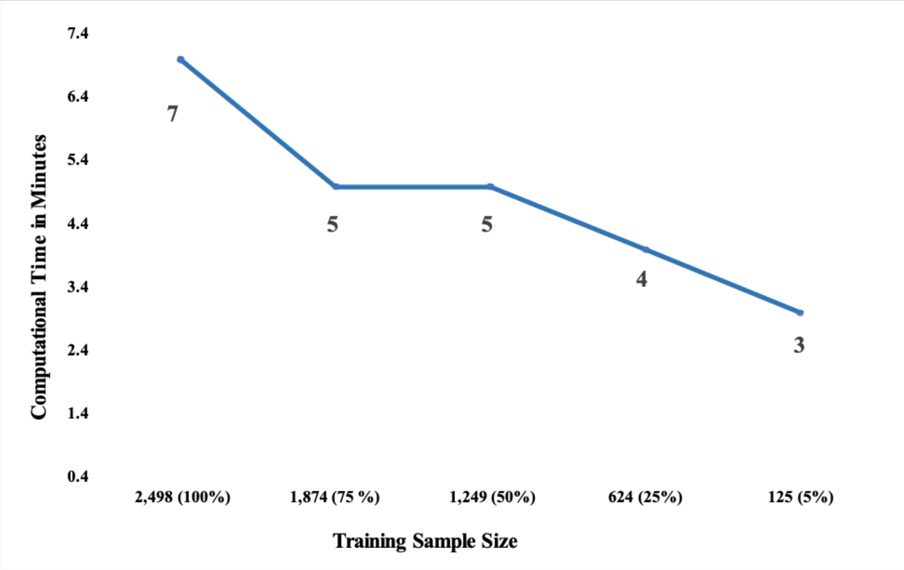


Computational Time Across Distinct Sample Sizes



"Masking" Tests

- Is ***BERT*** achieving **high accuracies** for the **wrong reasons**?

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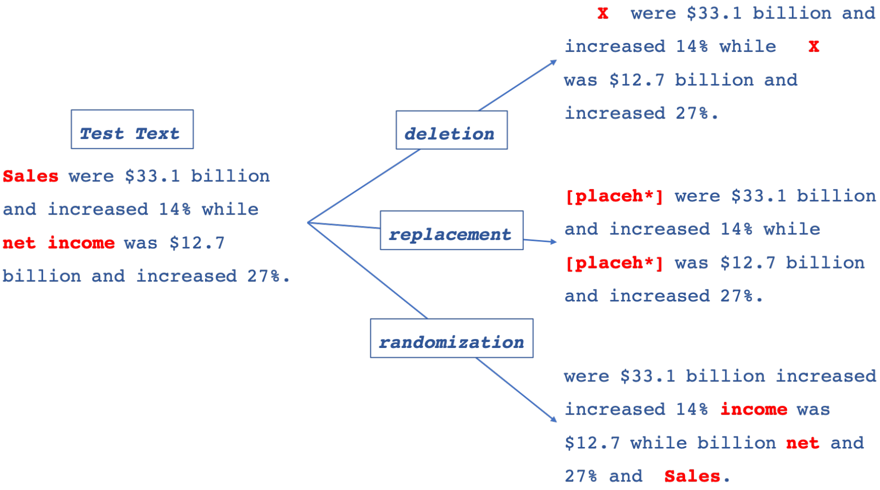

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BERT Model Prediction Accuracy on the "Masked" Text of Business Wire Q1 Earnings Announcements

Labeling Benchmark	Masking Test	Average Accuracy	Average AUC	Average F1	Total Observations
Median of y-o-y change in Quarterly Sales (by calendar quarter)	"Unmasked" 15-sentence Documents Benchmark	79%	78%	78%	625
	delete "I/income" and "N/net income"	75%	74%	76%	625
	delete "S/sales", "R/revenues" and "E/earnings"	74%	74%	77%	625
	delete "L/loss" and "L/losses"	68%	67%	75%	625
	delete "I/increase/s/d" and "D/decrease/s/d"	72%	71%	71%	625
	delete all numbers	71%	71%	71%	625
	replace "I/income" and "N/net income"	74%	73%	75%	625
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2. *BERT* seems to **provide** with a **feature representation** of text that captures **fundamental semantic connections in language**

3. Data proliferation, high power, modest resource intensiveness and easiness of use likely make **Transfer Learning a long-lasting phenomenon**

THANK YOU!