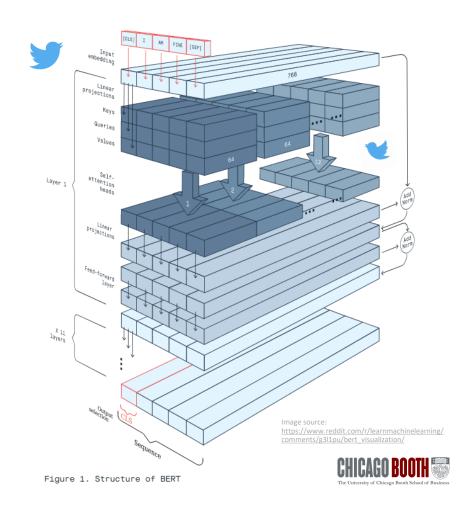
# Classifying Disaster Tweets with BERT



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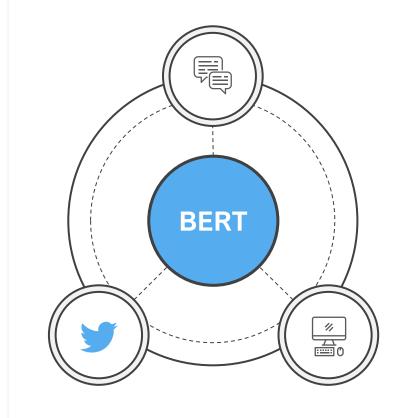
- Overview of the project
- Brief history of NLP and glimpse inside BERT
- Data pre-processing
- Model Comparison
   Decision Tree, Random Forest, Logistic Regression
- Evaluation, Conclusion, and Comments



#### Overview

Social Networking Service

Realtime Communication



Natural Language Processing

Programmatically Monitor Content

Machine Learning

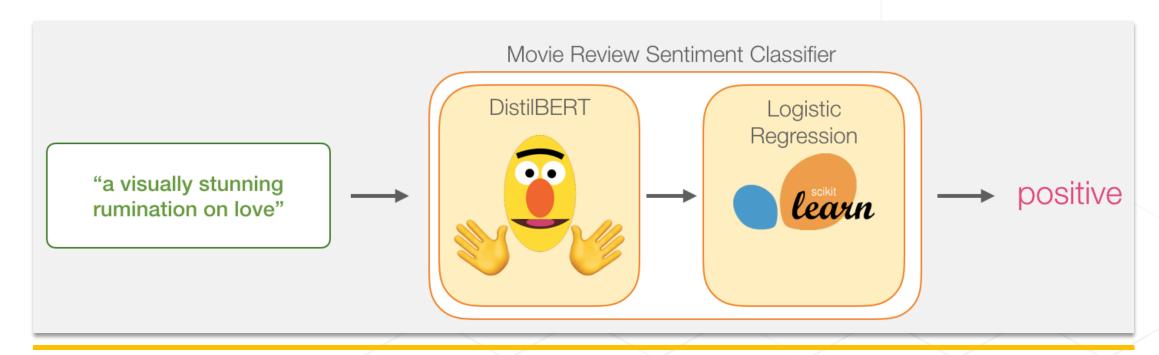
Predictive Algorithm



## What is BERT?

A Deep Neural Network (DNN) model

2018 published Bidirectional Encoder Representations from Transformers (BERT)



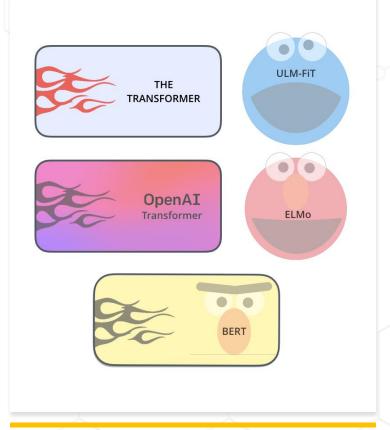




# A brief history of NLP and ML

- Bag of Words, TF, TF-IDF naïve counts
- Word2vec, GloVe context-free embeddings
- Transformer encoder-decoder structure
- **ELMo** contextualized embeddings
- OpenAI fine-tuning pretrained models

"BERT does it all, and better!"





# **Bidirectional Word Embeddings**

#### Context Matters!

One of the main advantages of BERT

Parallels with Convolutional Nets (fully connected)

0.1% Aardvark Use the output of the Possible classes: masked word's position All English words 10% Improvisation to predict the masked word 0% Zyzzyva FFNN + Softmax Randomly mask 15% of tokens [MASK]

"A New Age of Embedding"



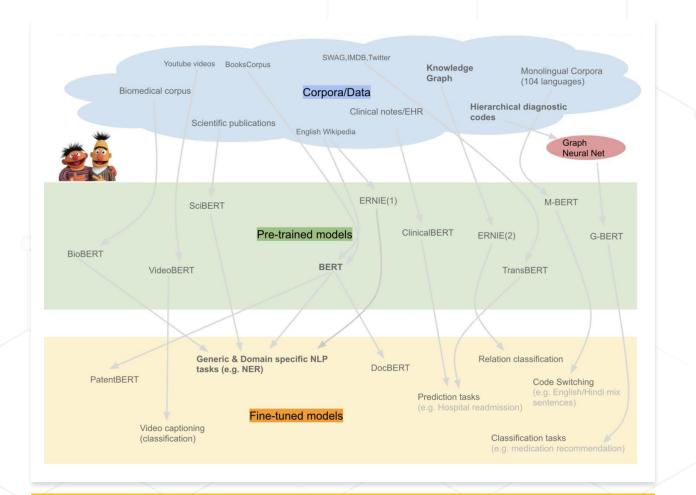
#### **Pretrained Models**

#### Massive datasets

Pre-trained models used more than 10,000 books plus Wikipedia data

#### Superb efficiency

BERT enables superior performance with minimal task-specific fine-tuning





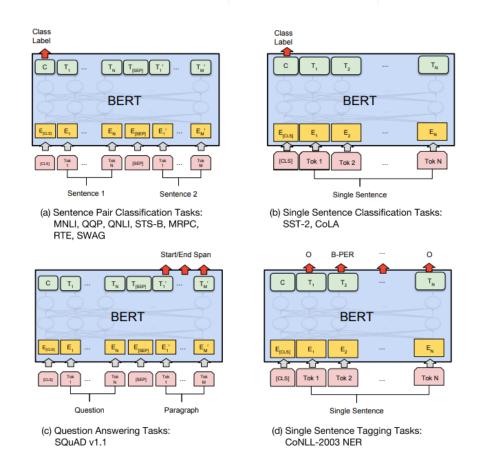
# Usage for different tasks

#### Numerous use cases

The authors of the original paper report a number of applications where BERT has powerful performance

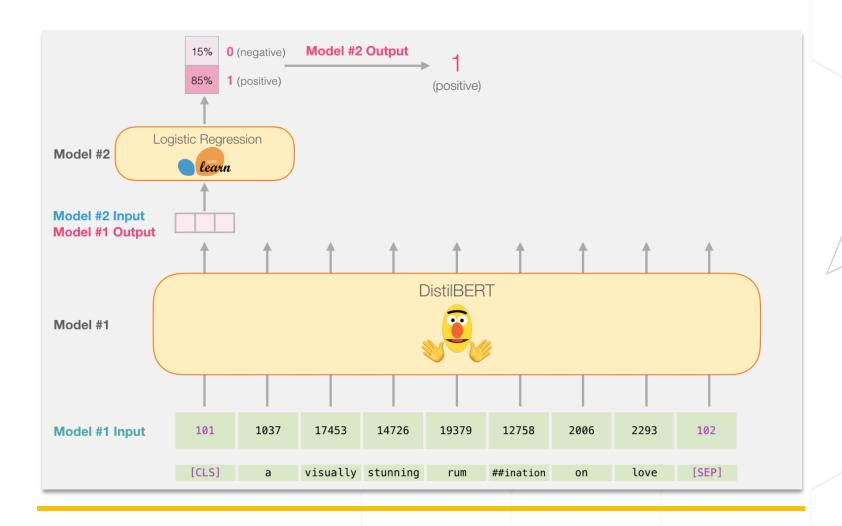
#### Versatile machine

BERT can handle single sentence, sentence pairs, question answer pairs, and paragraphs.





# Our task: Binary classification

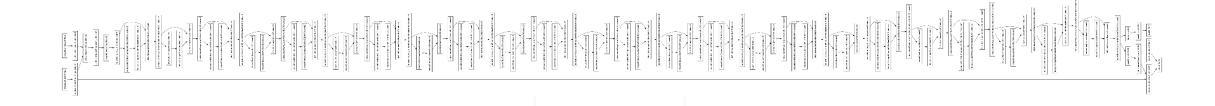


"Classifying whether a disaster-related tweet is about a real disaster!"



#### The architecture

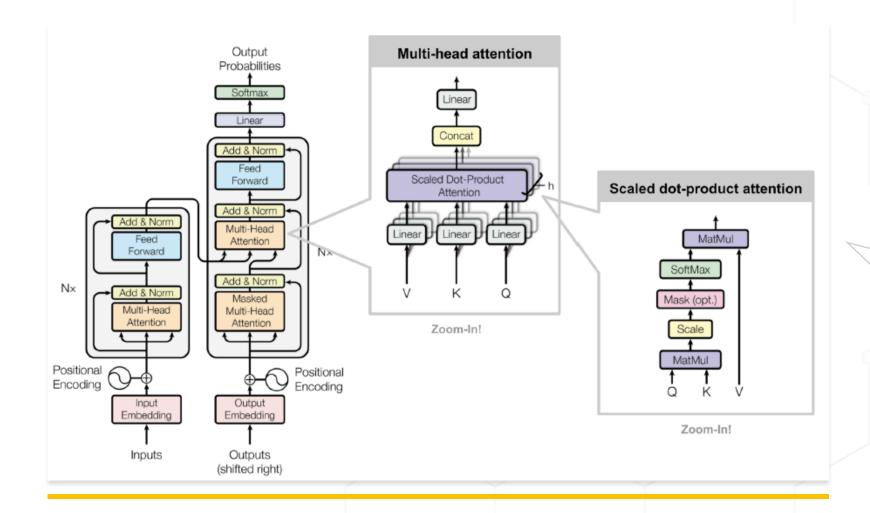
Below is not a DNA structure but BERT...



It takes time to understand... But we can take a glimpse at it!



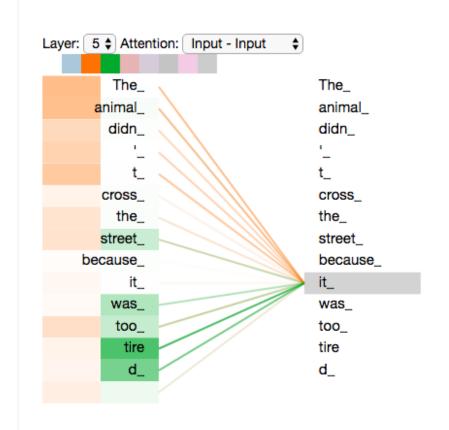
# High level overview



"It's a black box!"

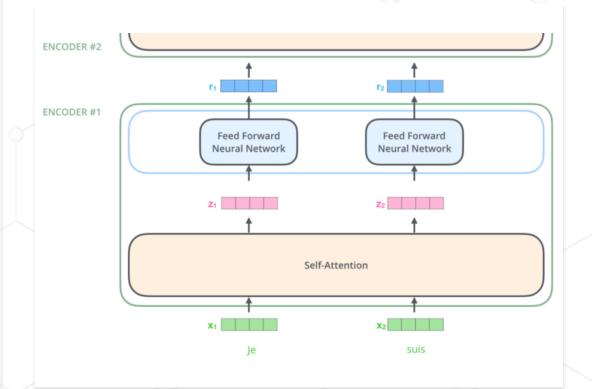


### The encoder (1/3)



#### Multi-head Attention

#### Feed-forward NN



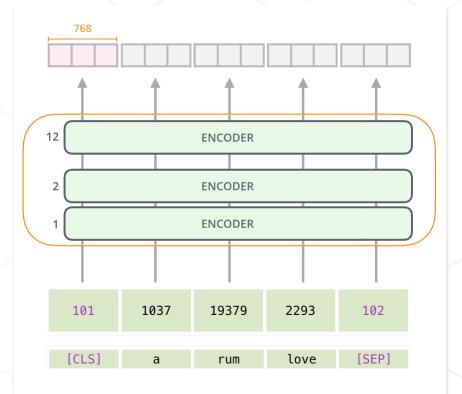


#### The encoder (2/3)

3) Split into 8 heads. 5) Concatenate the resulting Z matrices, 1) This is our 2) We embed 4) Calculate attention input sentence\* each word\* We multiply X or then multiply with weight matrix W° to using the resulting R with weight matrices produce the output of the layer Q/K/V matrices  $W_0^Q$ Thinking Machines Wo \* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one

"Math behind it..."

#### Use Last-hidden layer

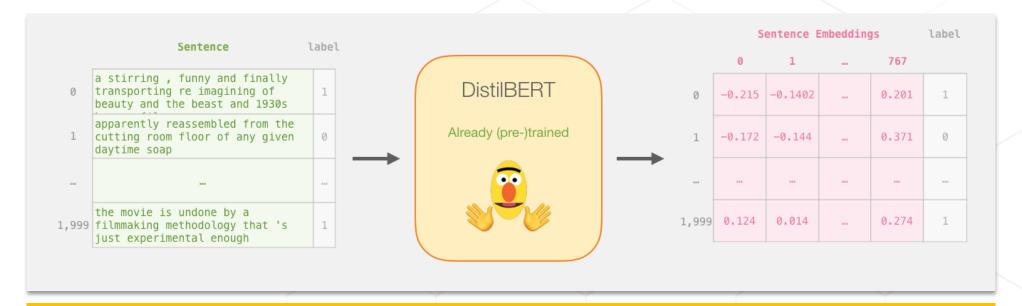




#### The encoder (3/3)

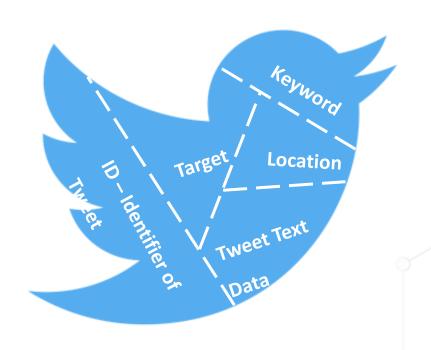
- Sentence embeddings can be retrieved from [CLS] token

  Tweets are vectorized while carrying the contextual information. Hence, contextual embeddings
- The embedding are fed into various ML algorithms to make predictions Classification Tree, Random Forest, Logistic Regression





# **Data Exploration**



• ID

Unique identifier for the tweet

Text

Text of the tweet

Location

Where the tweet was sent from (contains NA)

Keyword

Particular keyword from the tweet (contains NA)

Target

Indicate true disaster-related tweet



# Data (1/3) Original

	keyword	location	text	target
1	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	NaN	NaN	All residents asked to 'shelter in place' are	1
3	NaN	NaN	13,000 people receive #wildfires evacuation or	1
4	NaN	NaN	Just got sent this photo from Ruby #Alaska as	1
5	NaN	NaN	#RockyFire Update => California Hwy. 20 closed	1
195	ambulance	chicago	when you don't know which way an ambulance is	1
196	ambulance	NaN	#reuters Twelve feared killed in Pakistani air	1
197	ambulance	L. A.	http://t.co/pWwpUm6RBj Twelve feared killed in	1
198	ambulance	NaN	Why is there an ambulance right outside my work	0
199	ambulance	Canada	□ÛÏ@LeoBlakeCarter: This dog thinks he's an am	0



#### Data (2/3) Tokenized and Normalized

	keyword	location	text	tokenized	normalized
1	NaN	NaN	Forest fire near La Ronge Sask. Canada	['Forest', 'fire', 'near', 'La', 'Ronge', 'Sas	['forest', 'fire', 'near', 'la', 'ronge', 'sas
2	NaN	NaN	All residents asked to 'shelter in place' are	['All', 'residents', 'asked', 'to', "'shelter"	['all', 'residents', 'asked', 'to', 'in', 'pla
3	NaN	NaN	13,000 people receive #wildfires evacuation or	['13,000', 'people', 'receive', '#', 'wildfire	['people', 'receive', 'wildfires', 'evacuation
4	NaN	NaN	Just got sent this photo from Ruby #Alaska as	['Just', 'got', 'sent', 'this', 'photo', 'from	['just', 'got', 'sent', 'this', 'photo', 'from
5	NaN	NaN	#RockyFire Update => California Hwy. 20 closed	['#', 'RockyFire', 'Update', '=', '>', 'Califo	['rockyfire', 'update', 'california', 'hwy', '
195	ambulance	chicago 	when you don't know which way an ambulance is	['when', 'you', 'do', "n't", 'know', 'which',	['when', 'you', 'do', 'know', 'which', 'way',
196	ambulance	NaN	#reuters Twelve feared killed in Pakistani air	['#', 'reuters', 'Twelve', 'feared', 'killed',	['reuters', 'twelve', 'feared', 'killed', 'in'
197	ambulance	L. A.	http://t.co/pWwpUm6RBj Twelve feared killed in	['http', ':', '//t.co/pWwpUm6RBj', 'Twelve', '	['http', 'twelve', 'feared', 'killed', 'in', '
198	ambulance	NaN	Why is there an ambulance right outside my work	['Why', 'is', 'there', 'an', 'ambulance', 'rig	['why', 'is', 'there', 'an', 'ambulance', 'rig
199	ambulance	Canada	□ÛÏ@LeoBlakeCarter: This dog thinks he's an am	['\x89ÛI', '@', 'LeoBlakeCarter', ':', 'This',	['leoblakecarter', 'this', 'dog', 'thinks', 'h



# Data (3/3) BERT Embedding, Vectorized

	label	text	V0	V1	V2	<b>V</b> 3	V764	V765	V766	V767
1	1	Forest fire near La Ronge Sask. Canada	-0.221553	0.105736	0.177232	-0.060106	-0.112760	-0.048379	0.136526	0.247243
2	1	All residents asked to 'shelter in place' are	-0.306347	-0.045762	0.105919	-0.162701	-0.142231	0.002799	0.350246	0.166709
3	1	13,000 people receive #wildfires evacuation or	-0.198977	0.059032	0.068434	-0.208566	0.027611	0.014557	0.229373	0.303111
4	1	Just got sent this photo from Ruby #Alaska as	-0.204478	-0.069526	0.100186	-0.165095	-0.014447	-0.010891	0.234791	0.152992
5	1	#RockyFire Update => California Hwy. 20 closed	-0.236724	-0.057379	0.109873	-0.124354	-0.037461	0.132887	0.206636	0.252258
195	1	when you don't know which way an ambulance is	-0.255051	-0.122965	0.065260	-0.267028	0.018411	-0.021807	0.364001	0.285695
196	1	#reuters Twelve feared killed in Pakistani air	-0.266950	-0.270678	0.202017	-0.085696	0.052191	0.054019	0.258357	0.092139
197	1	http://t.co/pWwpUm6RBj Twelve feared killed in	-0.241344	-0.300067	0.194483	-0.069829	0.051480	0.097453	0.423019	-0.003391
198	0	Why is there an ambulance right outside my work	-0.260271	-0.088422	-0.099738	-0.424868	0.139882	-0.041099	0.529022	0.386493
199	0	□ÛÏ@LeoBlakeCarter: This dog thinks he's an am	-0.244549	-0.087695	0.099643	-0.156994	-0.052463	-0.012890	0.336068	0.125962



## Model comparison

Model Selection Criterion

Hyperparameter tuning and 5-fold CV, 1SE deviance

• Performance Measure

Confusion Matrix, F1-score

#### Algorithms

Distil BERT – Classification Tree

Distil BERT – Random Forest

Distil BERT – Logistic Regression

BERT-base Binary Classifier



# **Decision Tree**

	Prediction T	Prediction F	
Actual T	751	651	Sensitivity = 0.536
Actual F	Actual F 704		Specificity = 0.622
	Precision = 0.516	Neg-preci = 0.640	Accuracy = 0.578
		Total obs. = 3,263	F1 score = 0.526



# Random Forest

	Prediction T	Prediction F	
Actual T	868	534	Sensitivity = 0.619
Actual F	Actual F 382		Specificity = 0.795
	Precision = 0.694	Neg-preci = 0.630	Accuracy = 0.715
		Total obs. = 3,263	F1 score = 0.655



# Logistic Regression

	Predict T	Predict F	
Actual T	766	636	Sensitivity = 0.546
Actual F	439	1,422	Specificity = 0.764
	Precision = 0.636	Neg-preci = 0.691	Accuracy = 0.663
		Total obs. = 3,263	F1 score = 0.588





# **BERT Binary Classifier**

	Predict T	Predict F	
Actual T	959	443	Sensitivity = 0.684
Actual F	196	1,665	Specificity = 0.895
	Precision = 0.830	Neg-preci = 0.790	Accuracy = 0.810
		Total obs. = 3,263	F1 score = 0.750

#### Comments

- The outcome is based on Gelu activation and logit prediction
- Due to the hardware limitations, BERT-base was only trained 1 epoch while BERT-large was unable to be fine-tuned.



#### Final comments

#### Model Performances

BERT reported both the lowest type I and type II errors and outperformed the other models in every criteria, leading the second-best model by

- 9.5pp in overall accuracy, reporting 81%
- 0.095 in F-1 score, reporting 0.750

#### Improvements to be made

- start with the right device and train BERT-large
- scrape more data from twitter

#### A way to the future: Human first-Al

One of the implications for this project is a potential automated monitoring system that could be used as an alert system. And I would like to suggest that the alert system can be perfected with human touch.



#### References

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 https://arxiv.org/pdf/1810.04805.pdf

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<a href="http://jalammar.github.io/illustrated-bert/">http://jalammar.github.io/illustrated-bert/</a>

