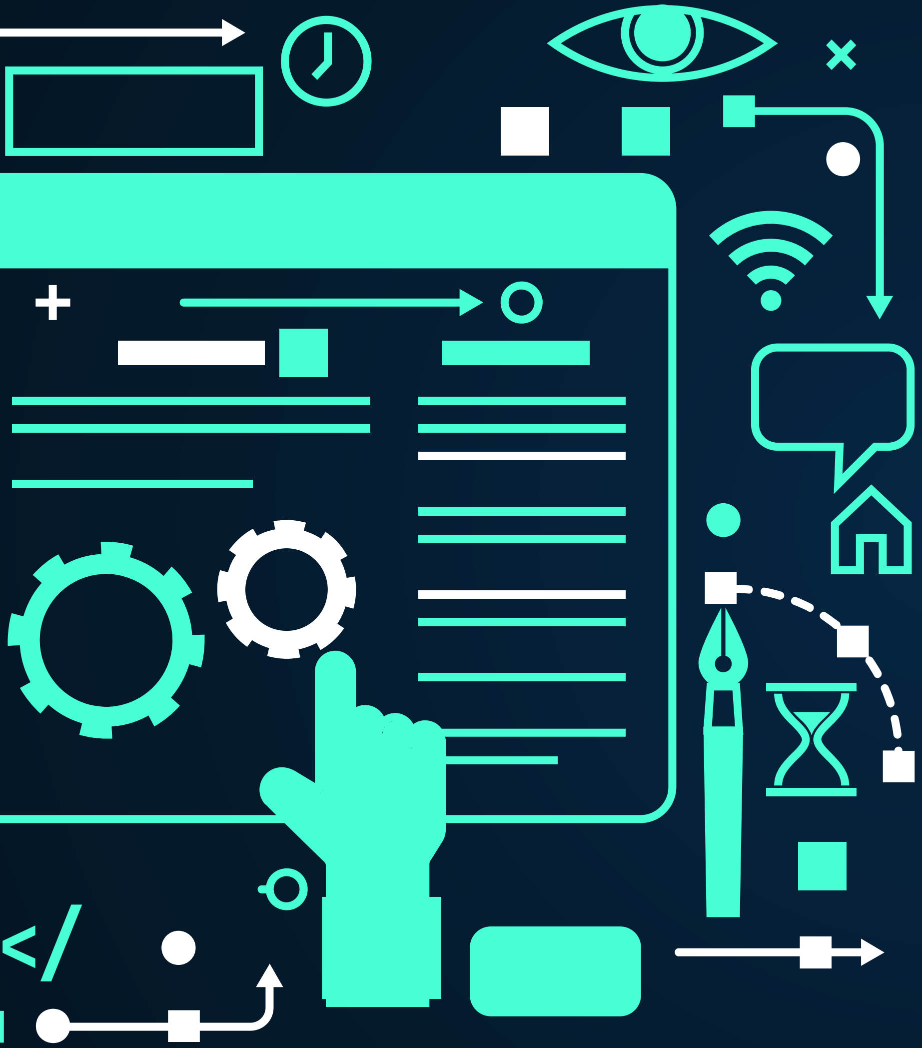

Gathering and Classification of Sports Injury Data

Presented By-
Jhagrut Lalwani,
Joe Datz

Problem Statement

We want to create a function:

$$H(X) \to Y$$

Where X is our dataset (text) and Y is our target variable (1 for injury report, 0 for not an injury report).

H(

Joe McDonald @JoeyMacHockey

I can't believe I actually just witnessed a ballpark engagement gone wrong. He asked and it appeared she said no. She ran off and he walked off in a different direction. That could be a first.

8:38 PM · Jul 15, 2021 · Twitter Web App

61 Retweets **64** Quote Tweets **830** Likes

) → 0

H(

Tim Stebbins @tim_stebbins

Ross and a trainer came out to check on Wisdom, who appeared to hurt his right leg taking an up-and-in offering.

Stays in game and hits a hard lineout to 3B.

8:29 PM · Jun 22, 2021 · Twitter Web App

1 Retweet **3** Likes

) → 1

AutoSave Off historical_mlb_injury_list - Read-Only Search Joe Dat JD

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Paste Cut Copy Format Painter Clipboard | Calibri 11 Font | Wrap Text Merge & Center Alignment | General Number | Conditional Formatting Format as Table Cell Styles Styles | Insert Delete Format Cells | AutoSum Fill Clear Sort & Filter Find & Select Editing | Analyze Data Analysis

POSSIBLE DATA LOSS Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in an Excel file format. Don't show again Save As...

I1 fx

	A	B	C	D	E	F	G	H	I
1	player_id	Entry Type	Current Date	injury_desc	injury_upd	injury_stat	due_back		
2	545358	Added	36:09.6	Recovering from September 2019 right hip surgery	Underwen	Spring Trai	2020		
3	605121	Current	36:09.6	Oblique strain	Shut down	Out Indefi	Mid-April		
4	596043	Current	36:09.6	Recovering from February 2020 right elbow surgery	Placed on	60-Day Inj	2020		
5	533167	Added	36:09.6	Recovering from April 2019 left ACL surgery	Underwen	Spring Trai	2020		
6	621366	Current	36:09.6	Left elbow tightness	Expected t	Day-to-day	Possibly late February		
7	430935	Current	36:09.6	Left shoulder soreness	Expected t	Spring Trai	Possibly April		
8	592833	Added	36:09.6	Recovering from March 2019 right knee surgery	Underwen	Spring Trai	2020		
9	608349	Current	36:09.6	Recovering from April 2019 Tommy John surgery	Underwen	Spring Trai	2020		
10	592387	Added	36:09.6	Recovering from August 2019 right hip surgery	Underwen	Spring Trai	2020		
11	571945	Current	36:09.6	Flexor tendon soreness in right arm	Underwen	Spring Trai	Possibly April		
12	663855	Current	36:09.6	Recovering from June 2019 Tommy John surgery	Underwen	60-Day Inj	Possibly 2020		
13	446399	Added	36:09.6	Carpal tunnel syndrome in left arm	Throwing l	Spring Trai	Possibly 2020		
14	519306	Added	36:09.6	Recovering from April 2019 left knee surgery	Underwen	Spring Trai	2020		
15	611093	Current	36:09.6	Recovering from March 2019 Tommy John surgery	Underwen	Spring Trai	2020		
16	467055	Current	36:09.6	Recovering from Sept. 2019 Tommy John surgery on right elbow	Ahead of s	Spring Trai	Possibly May		
17	606625	Current	36:09.6	Recovering from September 2019 right shoulder surgery	Underwen	60-Day Inj	Possibly late 2020		
18	605244	Current	36:09.6	Recovering from February 2020 right hip surgery	Underwen	Spring Trai	TBD		
19	542881	Current	36:09.6	Recovering from June 2019 left knee surgery	Rehabbing	Spring Trai	Possibly early 2020		
20	571980	Current	36:09.6	Recovering from September 2019 right knee surgery	Underwen	Spring Trai	2020		
21	605182	Current	36:09.6	Recovering from February 2020 left knee surgery	Out 6-8 we	Spring Trai	Possibly April		
22	571745	Current	36:09.6	Recovering from January 2020 sports hernia surgery, February 2020 back surgery	Out indefir	Spring Trai	2020		
23	613534	Current	36:09.6	Recovering from October 2019 right knee surgery	Placed on	60-Day Inj	Possibly 2020		
24	608716	Current	36:09.6	Recovering from August 2019 right elbow surgery	Had right e	Spring Trai	2020		
25	622098	Current	36:09.6	Recovering from March 2019 Tommy John surgery	Underwen	Spring Trai	2020		

historical_mlb_injury_list

Select destination and press ENTER or choose Paste 100%

Problem Statement

It is only at the top of this pyramid where data on injury information is publicly available. At all other levels, MLB teams have their data private.

We'd like to use twitter so that we may greatly expand the usable injury data for analysis.

Problem Statement

It is only at the top of this pyramid where data on injury information is publicly available. At all other levels, MLB teams have their data private.

We'd like to use twitter so that we may greatly expand the usable injury data for analysis.

Other important considerations:

- Utilize both labeled and unlabeled data. **(Semi-Supervised / Multi-View Learning)**
- Each cycle of gathering tweets and evaluating them preferably stays under 24 hours.

WEB SCRAPING PIPELINE

As Of This Writing:

- 2,200 Twitter Accounts
- 600,000 Tweets
- 15,000 Unique Labels

Results with Standard Models

Each model had:

- 8-fold Cross Validation
- Stratified Sampling over same dataset
- Stop word removal and word stemming

Model	Data Type	Results
kNN	TF-IDF	[[4060 92] [103 329]]
Bernoulli NB	Boolean	[[3972 180] [43 389]]
Multinom. NB	Count	[[3896 256] [34 398]]
Logistic Regression	TF-IDF	[[3997 155] [47 385]]
Random Forest	Boolean	[[3929 223] [68 364]]
Random Forest	TF-IDF	[[3939 213] [72 360]]
SVM	TF-IDF	[[4092 60] [87 345]]

Results with Standard Models

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- 8-fold Cross Validation
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A variant of PCA called IPCA was also experimented with to see how a Dense NN would work on the data. However, it failed to apply to our use case.

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Results with Standard Models

Best: **Multinomial Naive Bayes**

Reason: Lowest false negative rate (34)

In our use case, we would check the output of all our tweets the model output as a 1 (true positives and false positives) before adding to our injury record.

The False Negatives would be lost in the tens of thousands of 0 outputs, so we'd like to avoid this.

Model	Data Type	Results
kNN	TF-IDF	[[4060 92] [103 329]]
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SVM	TF-IDF	[[4092 60] [87 345]]

Results with Neural Networks

Each model had:

- Random samples of 6000 non-injury tweets to prevent imbalance issues
- Stop word removal and word stemming
- Stratified train-test split on injury_report.

Model	Epochs	Results	Sens.
XLNet	5	[[1485 32] [28 316]]	0.9212
DistilBERT	3	[[1491 26] [30 312]]	0.9122
RoBERTa	3	[[1472 48] [22 225]]	0.9109
XLM-RoBERTA	5	[[1475 46] [69 270]]	0.7964

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DistilBertConfig {
  "_name_or_path": "distilbert-base-uncased",
  "activation": "gelu",
  "architectures": [
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  ],
  "attention_dropout": 0.1,
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  "dropout": 0.1,
  "hidden_dim": 3072,
  "initializer_range": 0.02,
  "max_position_embeddings": 512,
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  "n_heads": 12,
  "n_layers": 6,
  "pad_token_id": 0,
  "qa_dropout": 0.1,
  "seq_classif_dropout": 0.2,
  "sinusoidal_pos_embds": false,
  "tie_weights_": true,
  "transformers_version": "4.9.2",
  "vocab_size": 30522
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XLNetConfig {
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  "architectures": [
    "XLNetLMHeadModel"
  ],
  "attn_type": "bi",
  "bi_data": false,
  "bos_token_id": 1,
  "clamp_len": -1,
  "d_head": 64,
  "d_inner": 3072,
  "d_model": 768,
  "dropout": 0.1,
  "end_n_top": 5,
  "eos_token_id": 2,
  "ff_activation": "gelu",
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  "layer_norm_eps": 1e-12,
  "mem_len": null,
  "model_type": "xlnet",
  "n_head": 12,
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  "pad_token_id": 5,
  "reuse_len": null,
  "same_length": false,
  "start_n_top": 5,
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  "summary_last_dropout": 0.1,
  "summary_type": "last",
  "summary_use_proj": true,
  "task_specific_params": {
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      "max_length": 250
    }
  },
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  "untie_r": true,
  "use_mems_eval": true,
  "use_mems_train": false,
  "vocab_size": 32000
}
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RobertaConfig {
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  "architectures": [
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  ],
  "attention_probs_dropout_prob": 0.1,
  "bos_token_id": 0,
  "eos_token_id": 2,
  "gradient_checkpointing": false,
  "hidden_act": "gelu",
  "hidden_dropout_prob": 0.1,
  "hidden_size": 768,
  "initializer_range": 0.02,
  "intermediate_size": 3072,
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  "max_position_embeddings": 514,
  "model_type": "roberta",
  "num_attention_heads": 12,
  "num_hidden_layers": 12,
  "pad_token_id": 1,
  "position_embedding_type": "absolute",
  "transformers_version": "4.9.2",
  "type_vocab_size": 1,
  "use_cache": true,
  "vocab_size": 50265
}
```

```
XLMRobertaConfig {
  "_name_or_path": "xlm-roberta-base",
  "architectures": [
    "XLMRobertaForMaskedLM"
  ],
  "attention_probs_dropout_prob": 0.1,
  "bos_token_id": 0,
  "eos_token_id": 2,
  "gradient_checkpointing": false,
  "hidden_act": "gelu",
  "hidden_dropout_prob": 0.1,
  "hidden_size": 768,
  "initializer_range": 0.02,
  "intermediate_size": 3072,
  "layer_norm_eps": 1e-05,
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  "model_type": "xlm-roberta",
  "num_attention_heads": 12,
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  "output_past": true,
  "pad_token_id": 1,
  "position_embedding_type": "absolute",
  "transformers_version": "4.9.2",
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  "vocab_size": 250002
}
```

Results with Neural Networks

DistilBERT: faster inference speed with slightly poor prediction metrics

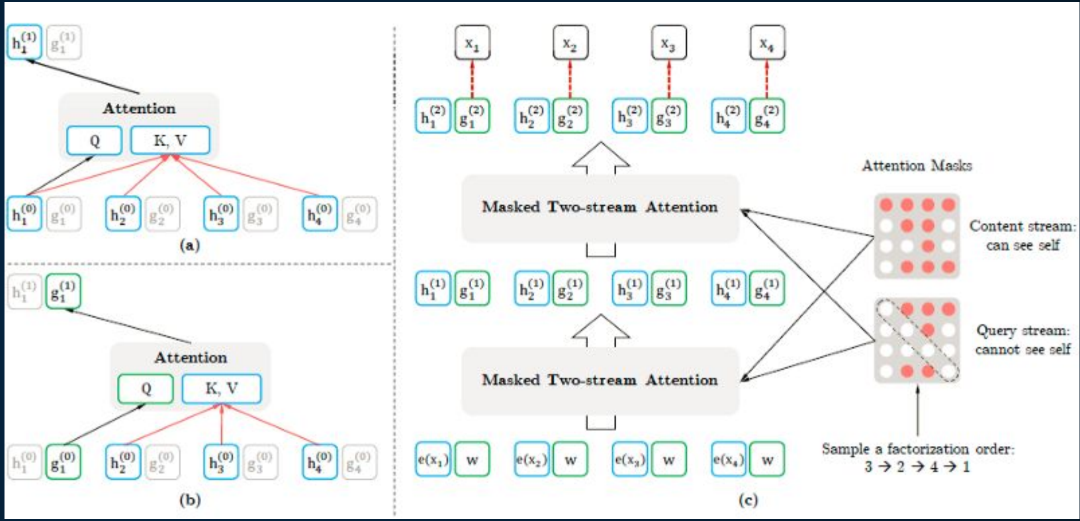
XLNet: permutation based training handles dependencies well

Models	Sensitivity	Accuracy	Precision	mcc	Selectivity	F1 score
XL-Net	0.9186	0.9678	0.979	0.8935	0.979	0.9133
RoBERTa	0.911	0.9604	0.8242	0.8437	0.9684	0.8564
Distil-BERT	0.9123	0.9699	0.923	0.8992	0.9829	0.9176
LSTM	0.8863	0.9731	0.965	0.909	0.9927	0.924
GRU	0.8338	0.9613	0.9502	0.8676	0.9901	0.8882
XLM-RoBERTa	0.7965	0.9382	0.8544	0.7877	0.9698	0.8244

Results with Neural Networks

DistilBERT: faster inference speed with slightly poor prediction metrics

XLNet: Uses a modified language model training objective which learns conditional distributions for all permutations of tokens in a sequence. Permutation based training handles dependencies well



Thank you!