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Transfer Learning in NLP

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Helping Small Teams Account
for Small Datasets

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Transfer Learning in NLP

- What we'll cover
 - A look into a real problem involving NLP and Deep Learning
 - A brief discussion of the pros and cons of methods we tried
 - How Transfer Learning can help **small teams with less data** compete with established corporations
 - A look at our results from applying these methods

Wootric - What We Do

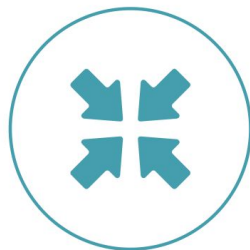
Collection



Track core CX metrics with micro-surveys that customers love

- Right question: NPS, CSAT, CES
- Right channel
- Right time

Analysis



Aggregate feedback from any source into one dashboard

- Autocategorization
- Sentiment analysis
- Algorithms tailored by industry

Action



Align the company around a single source of customer truth

- Deep & broad integrations
- Routing for action

Wootric - Problem We Want Solved

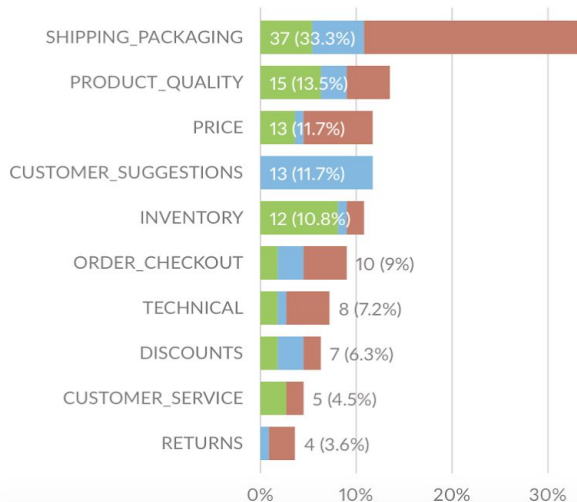
- Survey collects a lot of feedback
 - What set of topics is the customer commenting on?
 - Multi-Label Classification
 - How does the customer feel about the product/service?
 - Sentiment Analysis

Wootric - Problem We Want Solved

FEEDBACK BREAKDOWN

Visualize the % of selected feedback that contains specific tags, sentiment, and properties.

Tags



111 matches ● Positive sentiment ● Neutral sentiment ● Negative sentiment

enjoyed my first order, if nothing goes wrong in shipping, happy to recommend twbdjn500@njjwplzcjj500.tjtn
12 Jan 2019 / 16:00pm
nps 9

⚡ SHIPPING_PACKAGING ✕ +

I just love y'all so much for the cute decor! bzejttz.j@wjndstrjzm.tjtn
11 Jan 2019 / 16:00pm
nps 9

+

Last experience wasn't great, but this time was okay ljndz.trzng9677@sbmjijsp.zj
10 Jan 2019 / 16:00pm
nps 7

+

More than half my total was shipping, this is my last order judymzyjrr@zyybb.zj
9 Jan 2019 / 16:00pm
nps 6

⚡ PRICE ✕ ⚡ SHIPPING_PACKAGING ✕ +

New lamp looks gorgeous thanks! jzncjjszntbrb0222@sbmjij
8 Jan 2019 / 16:00pm
nps 9

⚡ PRODUCT_QUALITY ✕ +



Metrics to Evaluate

- Precision
 - Given we have “tagged” a piece of feedback, how often are we correct
- Recall
 - What percent of the feedback that we should tag are we actually tagging
- F1-Score
 - Combination of the two
 - $F1\text{-Score} = 2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$
 - We will report this for discussing model quality

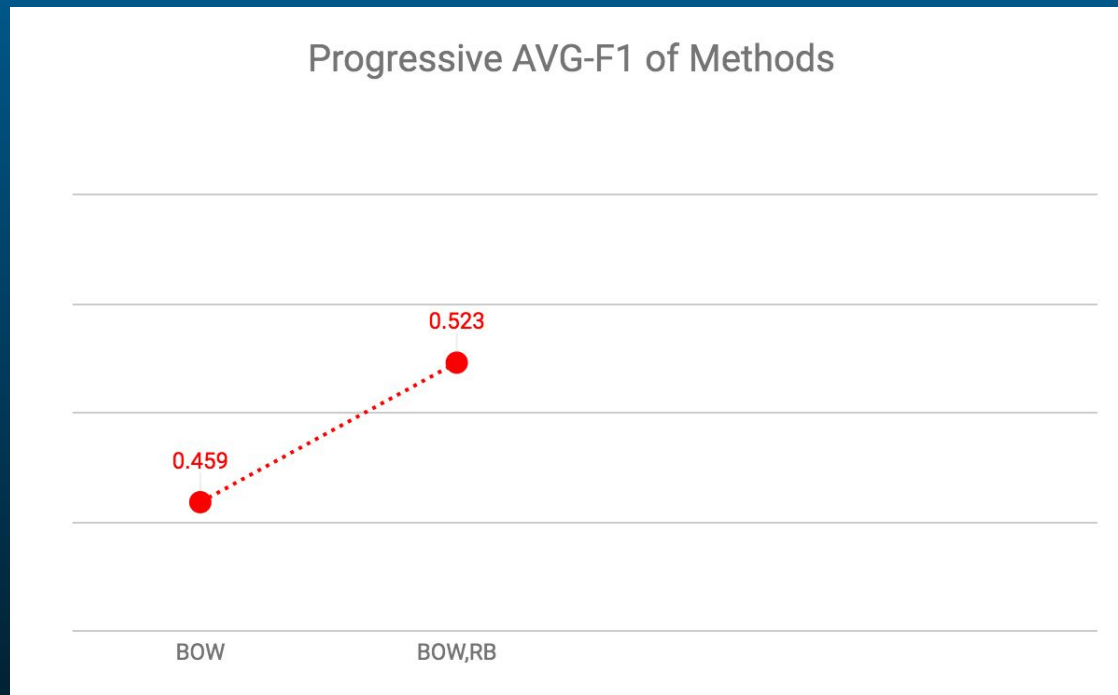
Applying ML

- Formal Problem:
 - “Given this piece of feedback and its industry, what tags should be applied?”
 - Multi-Label Classification: Applying a set of binary labels
 - Metrics: Precision, Recall, F1-Score **for each tag**
- For Business, it is nice to implement Low-Cost solutions first
 - A very basic model
 - An existing service

Using a Basic Model

- Models
 - Bag of Words
 - Rule Based
- Gives a good baseline
- Can keep iterating
- Requires that you have a production system in place

Using a Basic Model - Results



Using a Basic Model - Problems

- Language is hard to model
 - “The engineering **cost** to implement your product was too high”
 - Rule Based & BOW methods would tag as Price (incorrect)
 - “I really hate how much I love your product”
- Bag of Words and Rule Based approaches could be improved

Using an Existing Service

- Google Prediction API
 - Easy Interface
 - Had Binary or Multi-Class options
 - Used one classifier per tag, since our problem is Multi-Label
- Gave better results than BOW
 - Passed the baseline!

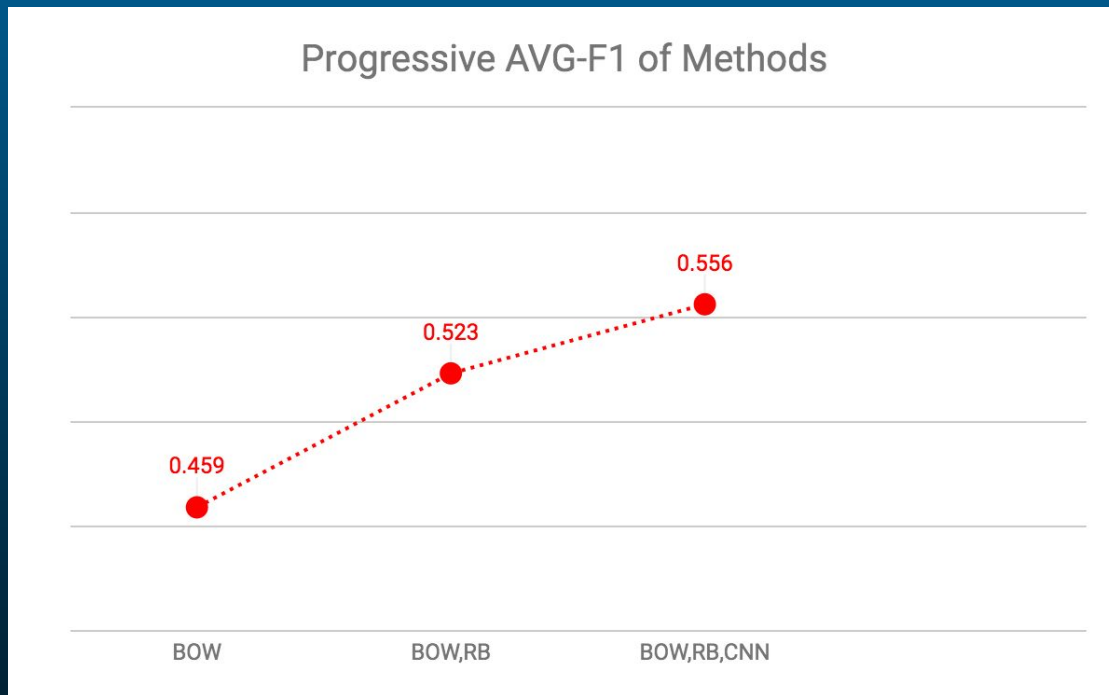
Problems

- Unfortunately, Prediction API began failing regression tests
 - Training process no longer gave good results
 - Google deprecated it soon after
 - AutoML did not come out until another year down the road
- Problem with black box systems: You have no control
- Now we only have basic methods, need better accuracy

Applying Deep Learning

- Deep learning is fun!
 - But (relatively) time consuming
 - Want to make sure it's worth the time investment
- Used basic CNN and LSTM models
 - CNN did well
 - LSTM was not effective

Applying Deep Learning - Results



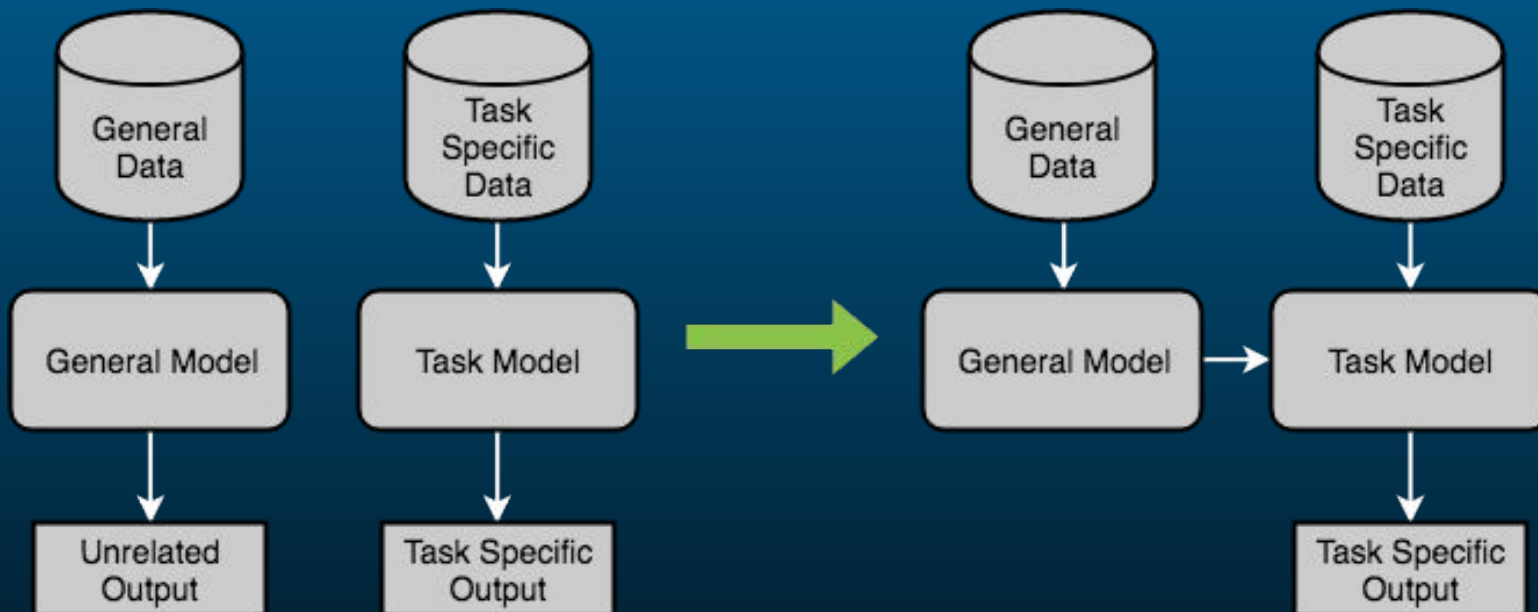
Problems - Small Training Set

- Have a lot of Feedback
 - Manually labeling is time consuming
- Class Imbalance Problem
 - Makes each additional chunk of labeled data less effective
- How can we learn from so few examples?
 - And still compete with models that use hundreds of thousands of training rows

Transfer Learning

- Want to make use of as much data as possible
- A model trained on a separate domain **can still be useful**

Transfer Learning



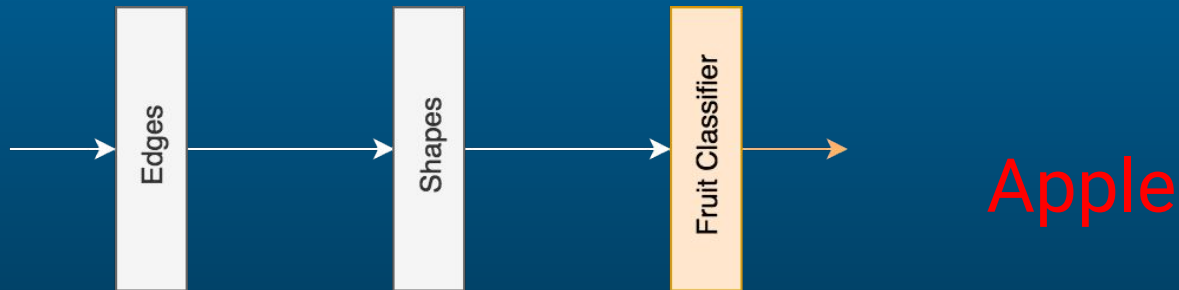
Transfer Learning

- More Data is better but how do we utilize it?
- Common Techniques include
 - Using parts of ImageNet models
 - Prior distribution for Bayesian Analysis
 - Word Vectors
 - Language Models (Just Recently)

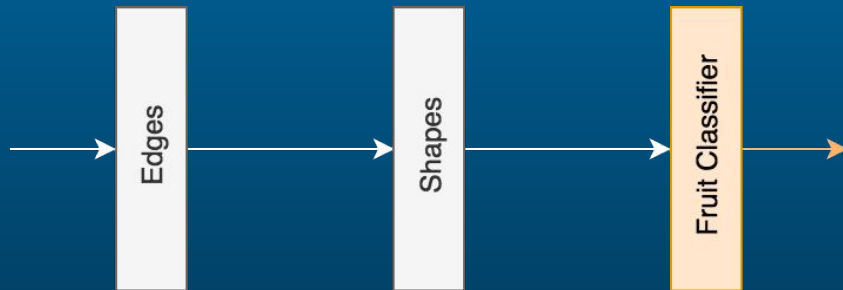
Transfer Learning in Computer Vision

- ImageNet
 - Learn low-level features from general data
 - Edges, shapes, colors, etc.
 - Build new classifiers on top for domain-specific tasks

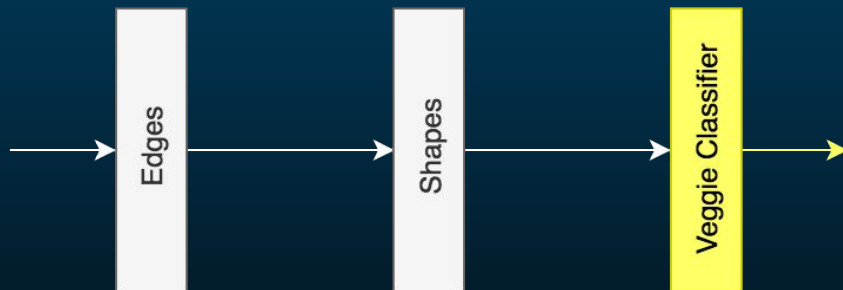
Transfer Learning in Computer Vision



Transfer Learning in Computer Vision



Apple



Broccoli

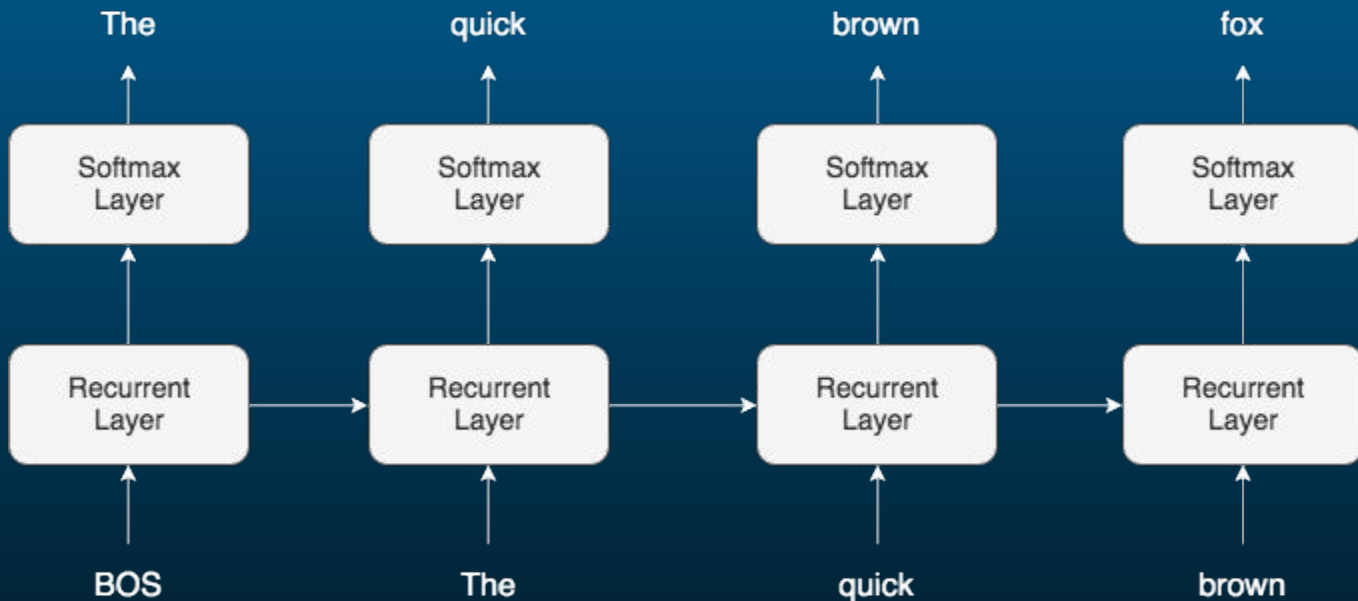
Transfer Learning in NLP

- Word Vectors
 - Huge stride in 2012
 - Learn **One Initial Layer** of a model
 - Only captures one aspect of language
 - Infamous GoogleNews generated word vectors

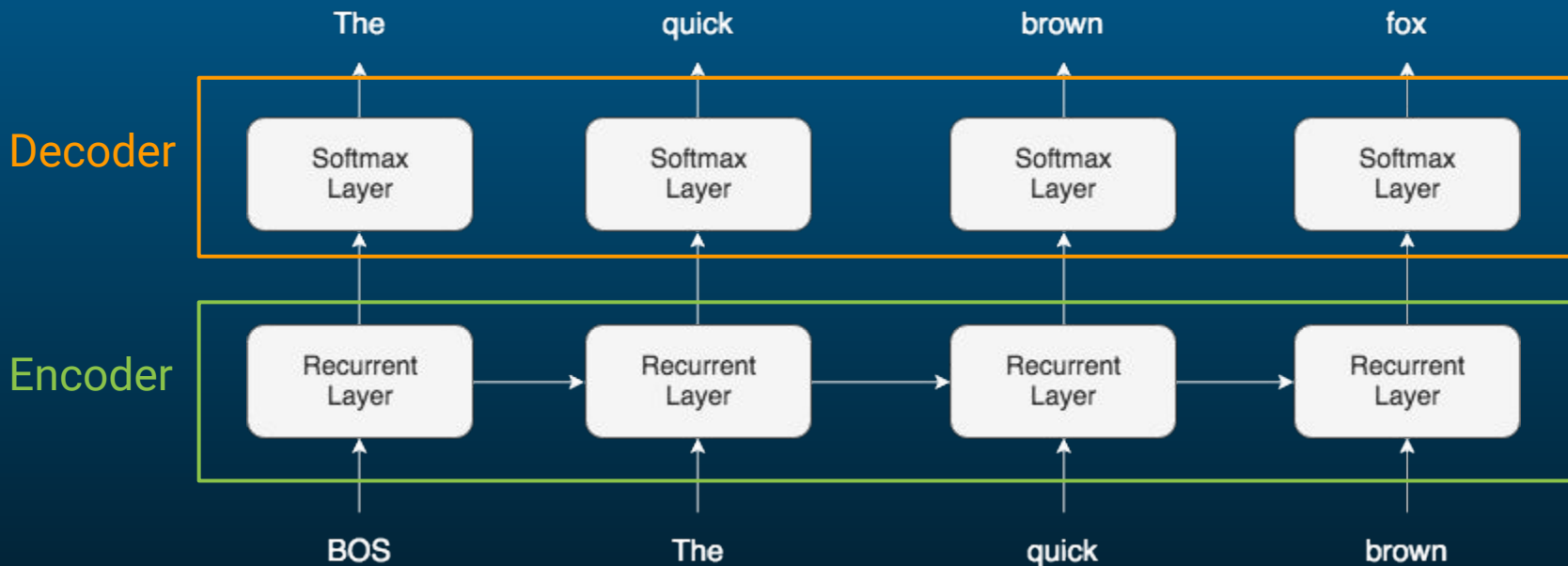
Transfer Learning in NLP

- Language Models
 - Learn **Multiple General Purpose Layers**
 - Trained to model language, not just words
 - A good Language Model will differentiate word sense
 - “I **hit** the ball”
 - “Our website got a lot of **hits**”
 - Order of words matters
 - **No labeled training data needed**

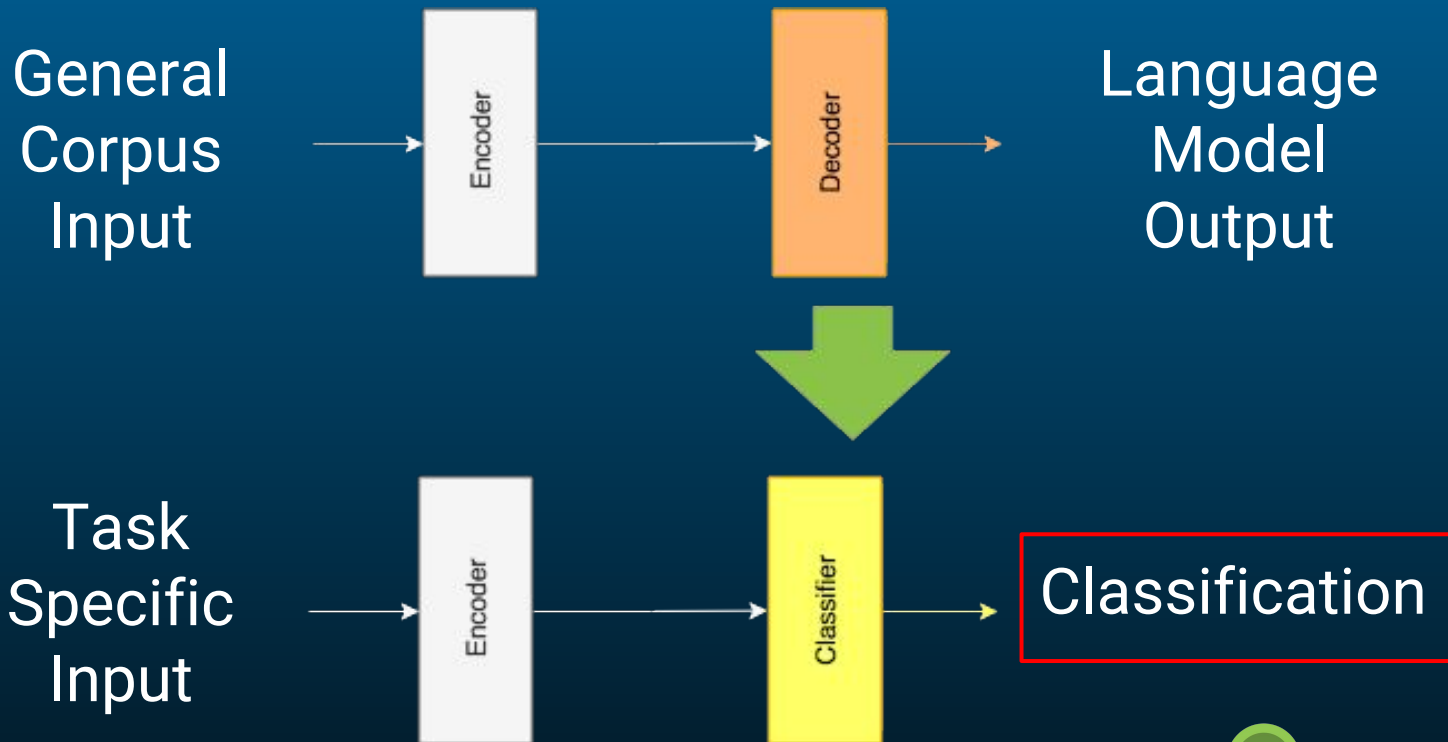
What is a Language Model?



What is a Language Model?



Building from Language Models



Building from Language Models

- **Initialize Model State** for your next task with the **Encoder of the More General Task**
- Can iterate this process as much as necessary
 - Don't need to settle for one general purpose Language Model
 - Use progressively more relevant corpuses to fine tune the language you will see in your data
 - Add a classifier for the last step, on your labeled data

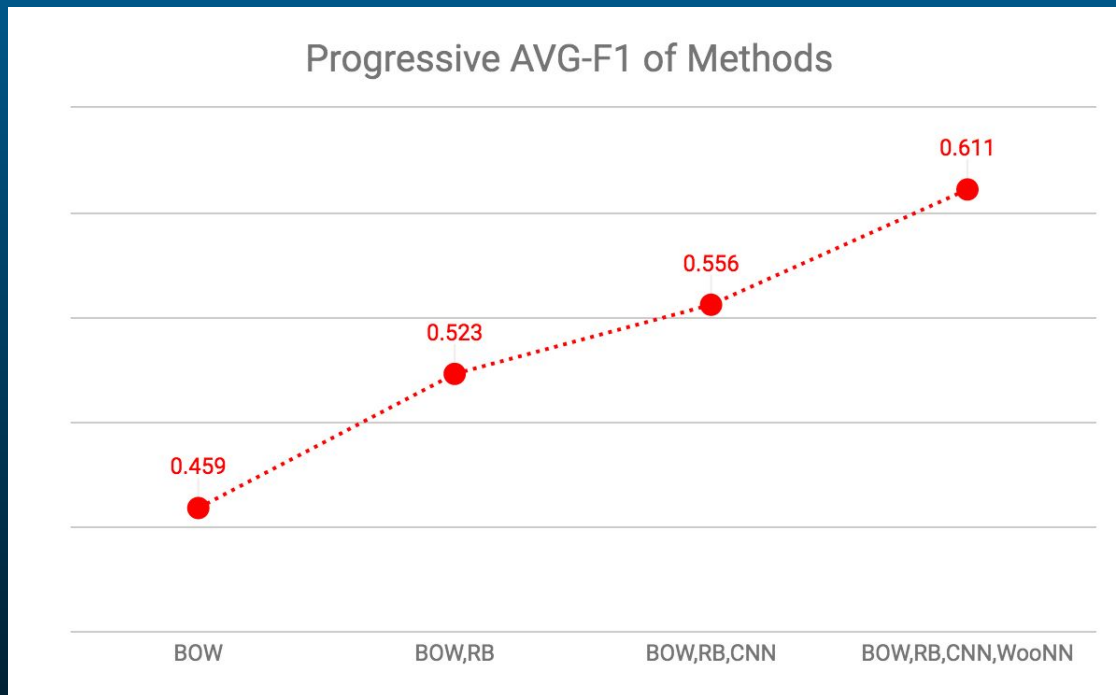
Transfer Learning in NLP

- “NLP’s Imagenet Moment”
 - Finally, we can use Transfer Learning to quickly productize DL models for NLP
- Can make use of publicly available text (and models)
 - Wiki-Text
 - Penn TreeBank
 - Twitter Stream
 - Web Crawl

Our Transfer Learning Model

1. Language Model over WikiText-103
 - There are pre-existing versions of these
2. Refine the Language Model on our (unlabeled) corpus
 - Adapts to the Customer Feedback domain
3. Train on our specific labeled data

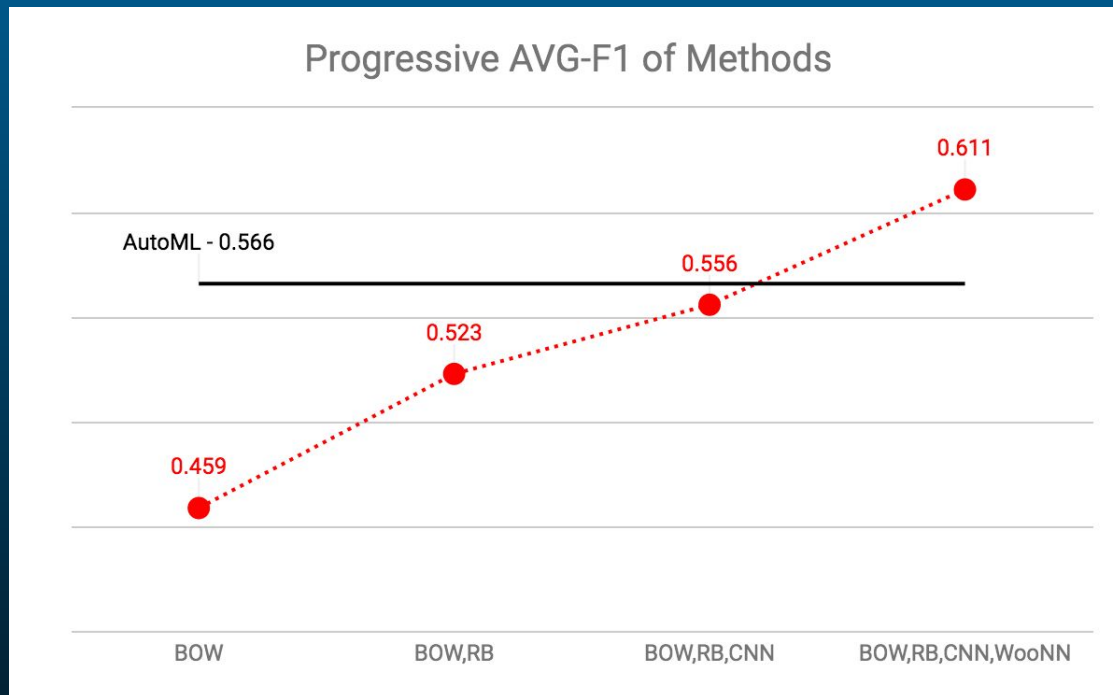
Our Transfer Learning Model - Results



AutoML

- AutoML came out after we got used to not having the Google Prediction API anymore
- Needed to compare our own models to see how we did

AutoML - Results



Sentiment Model

- Sentiment model is also important
 - We use it in determining Aspect-Based Sentiment Analysis for our tags
 - Trained on our own (smaller) dataset
 - Language Model pre-trained with Customer Feedback corpus
- 96.5% accuracy (WooNN) vs. 92% accuracy (Google NL API Sentiment)
 - Just because Google is Google doesn't mean you can't beat them in your own domain

Conclusion

- Evaluate if you need DL/Transfer Learning first
- We often have access to general, unspecified data
 - Combine with small, specific data to succeed in your domain
- Make use of as many building blocks that can transfer as possible

References

- “NLP’s ImageNet Moment has Arrived” - Sebastian Ruder
<https://thegradient.pub/nlp-imagenet/>
- “Universal Language Model Fine-tuning for Text Classification” - Jeremy Howard, Sebastian Ruder
<https://arxiv.org/abs/1801.06146>

Questions
