Human Language Technologies

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0.1 Introduction

Prof. Giuseppe Attardi
Prerequisites are: proficiency in Python, basic probability and statistics, calculus and linear algebra and notions of machine learning.

What will we learn Understanding of and ability to use effective modern methods for **Natural Language Processing**. From traditional methods to current advanced ones like RNN, Attentions...
Understanding the difficulties in dealing with NL and the capabilities of current technologies, with experience with **modern tools** and aiming towards the ability to build systems for some major NLP tasks: word similarities, parsing, machine translation, entity recognition, question answering, sentiment analysis, dialogue system...

Books Speech and Language Processing (Jurafsky, Martin), Deep Learning (Goodfellow, Bengio, Courville), Natural Language Processing in Python (Bird, Klein, Loper)

Exam Project (alone or team of 2-3 people) with the aim to experiment with techniques in a realistic setting using data from competitions (Kaggle, CoNLL, SemEval, Evalita...). The topic will be proposed by the team or chosen from a list of suggestions.

Experimental Approach

1. Formulate hypothesis
2. Implement technique
3. Train and test
4. Apply evaluation metric
5. If not improved:

   Perform error analysis

   Revise hypothesis
6. Repeat!

Motivations Language is the most distinctive feature of human intelligence, **it shapes thought**. Emulating language capabilities is a scientific challenge, a **keystone for intelligent systems** (see: Turing test)

Structured vs unstructured data The majority of **information shared with each other is unstructured**, primarily text. Information is mostly communicated by e-mails, reports, articles, conversations, media... and attempts to turn text to structured (HTML) or microformat only scratched the surface of **structuring unstructured information**.
Problems: requires universal agreed **ontologies** and additional effort. **Entity linking** attempts to provide a bridge.

0.2 State of the Art

Early History During 1950s, up until AI winter.

Resurgence in the 1990s Thanks to statistical methods, novelty, with the goal of **studying language**. Challenges arise: NIST, Netflix, DARPA Grand Challenge...
During 2010s: deep learning, neural machine translation...

Statistical Machine Learning Supervised training with **annotated** documents.
The paradigm is composed of the following:

Training set, composed of labeled data $\{x_i, y_y\}$

Representation: choose a set of features to represent data $x \mapsto \phi(x) \in R^D$

Model: choose an hypothesis function to compute $f(x) = F_\Theta(\phi(x))$

Evaluation: define the cost function on error with respect to examples $J(\Theta) = \sum_i (f(x_i) - y_i)^2$

Optimization: find parameters Θ that minimize $J(\Theta)$

It's a **generic method**, applicable to any problem.

Traditional Supervised Learning Approach Freed us from devising algorithms and rules, requiring the creation of annotated training sets and imposing the tyranny of feature engineering.
Standard approach for each new problem:

Gather as much labeled data as one can

Throw a bunch of models at it

Pick the best

Spend hours hand engineering some features or doing feature selection/dimensionality reduction

Rinse and repeat

Technological Breakthroughs Improved ML techniques but also large annotated datasets and more computing power, provided by GPUs and dedicated ML processors (like the TPU by Google).
ML exploits parallelism: stochastic gradient descent can be parallelized (asynchronous stochastic gradient descent). No need to protect shared memory access, and low (half, single) precision is enough.

Deep Learning Approach Was a big breakthrough.

Design a model architecture

Define a loss function

Run the network letting the parameters and the data representations **self-organize** as to minimize the loss

End-to-end learning: no intermediate stages nor representation

Feature representation Use a vector with each entry representing a feature of the domain element
Deep Learning represents data as vectors. Images are vectors (matrices), but words? **Word Embeddings**: transform a word into a vector of hundreds of dimensions capturing many subtle aspects of its meaning. Computed by the means of **language model**.
From a discrete to distributed representation. Words meaning are dense vectors of weights in a high dimensional space, with algebraic properties.
Background: philosophy, linguistics and statistics ML (feature vectors).

Language Model Statistical model which tells the probability that a word comes after a given word in a sentence.

Dealing with Sentences A sentence is a sequence of words: build a representation of a sequence from those of its words (compositional hypothesis). Sequence to sequence models.
Is there more structure in a sentence than a sequence of words? In many cases, tools forgets information when translating sentences into sequences of words, discarding much of the structure.

0.3 Language Modeling

Probabilistic Language Model The **goal is to assign a probability score to a sentence**.

> **Machine Translation**: $P(\text{high winds tonight}) > P(\text{large winds tonight})$
>
> **Spell Correction**: $P(\text{about fifteen } \underline{\text{minutes}} \text{ from}) > P(\text{about fifteen } \underline{\text{minuets}} \text{ from})$
>
> **Speech Recognition**: $P(\text{I saw a van}) > P(\text{eye saw a van})$
>
> **Language Identification**: s from unknown language (italian or english) and Lita, Leng language models for italian and english $\Rightarrow L\text{ita}(s) > L\text{eng}(s)$
>
> Summarization, question answering...

We want to compute

> $P(W) = P(w_1, w_2, \ldots, w_n)$ the probability of a sequence
>
> $P(w_4 \mid w_1, w_2, w_3, w_4)$ the probability of a word given some previous words

The model that computes that is called the **language model**

Markov Model and N-Grams Simplify the assumption: the probability of a word given all the previous is the same of the probability of that word given just few (one, two...) previous words. So $P(w_i | w_{i-}, \ldots, w_1) = P(w_i | w_{i-1})$ (First order Markov chain).
With a N**-gram**: $P(w_n \mid w_1^{n-1}) \simeq P(w_n \mid w_{n-N+1}^{n-1})$
In general it's insufficient: language has **long distance dependencies**, but we can often get away with N-gram models. For example:

> "The **man** next to the large oak tree near the grocery store on the corner **is** tall."
>
> "The **men** next to the large oak tree near the grocery store on the corner **are** tall."

Or even semantic dependencies:

> "The **bird** next to the large oak tree near the grocery store on the corner **flies** rapidly."
>
> "The **man** next to the large oak tree near the grocery store on the corner **talks** rapidly."

So more complex models are needed to handle such dependencies.

Maximum likelihood estimate

$$P(w_n \mid w_{n-N+1}^{n-1}) = \frac{\text{count}(w_{n-N+1}^{n-1}, w_n)}{\text{count}(w_{n-N+1}^{n-1})}$$

Maximum because it's the one that maximize $P(\text{Training set} \mid \text{Model})$

Shannon Visualization Method Generate random sentences:

> Choose a random bigram (`<s>`, w) according to its probability
>
> Choose a random bigram (w, x) according to its probability
>
> Repeat until we pick `</s>`

Shannon Game Generate random sentences by selecting the words according to the probabilities of the language models.

```
def gentext(cpd, word, length=20):
  print(word, end = ' ')
  for i in range(length):
    word = cpd[word].generate()
    print(word, end = ' ')
  print("")
```

Perils of Overfitting N-grams only work well for word prediction if the test corpus looks like the training corpus. In real life, this is often not the case.
We **need to train robust models able to adapt**.

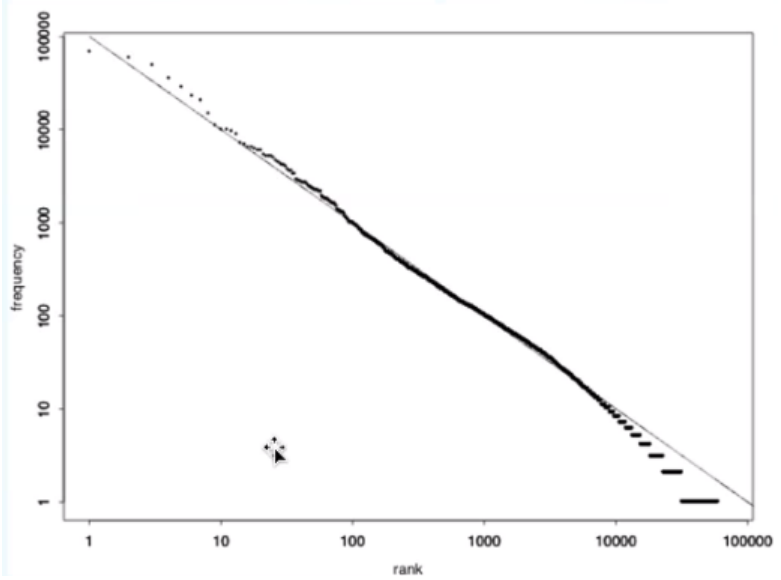
Smoothing Many rare (but not impossible) combinations of word sequences never occur in training, so MLE incorrectly assigns zero to many parameters (sparse data).
If a new combination occurs during testing, it is given a probability of zero and the entire sequence gets a probability of zero (infinite perplexity).
Parameters are **smoothed**/regularized to reassign some probability mass to unseen events (meaning removing probability from seen ones in order to maintain the joint distribution that sums to 1)

Zipf's Law A small number of events occur with high frequency, while a large number of events occur with small frequency. You can quickly collect statistics on the high frequency events, but you may have to wait an arbitrarily long time to get valid statistics on low frequency events.
The result is that our estimates are sparse. No counts at all for the vast bulk of things we want to estimate. Some of the zeroes in the table are really zeroes, but others are simply low frequency events you haven't seen yet: after all, anything can happen. How to address? By estimating the likelihood of unseen N-grams.

Word	Freq. (f)	Rank (r)	$f \cdot r$
the	3332	1	3332
and	2972	2	5944
a	1775	3	5235
he	877	10	8770
but	410	20	8400
be	294	30	8820
there	222	40	8880
one	172	50	8600
about	158	60	9480
more	138	70	9660
never	124	80	9920
Oh	116	90	10440
two	104	100	10400

Word	Freq. (f)	Rank (r)	$f \cdot r$
turned	51	200	10200
you'll	30	300	9000
name	21	400	8400
comes	16	500	8000
group	13	600	7800
lead	11	700	7700
friends	10	800	8000
begin	9	900	8100
family	8	1000	8000
brushed	4	2000	8000
sins	2	3000	6000
Could	2	4000	8000
Applausive	1	8000	8000

Result: f is proportional to $\frac{1}{r}$, meaning that there is a constant $k \mid f \cdot r = k$



0.3.1 Evaluation and Perplexity

Evaluation Train parameters of our model on a training set. For the evaluation, we apply the model on new data and look at the model's performance: **test set**. We need a metric which tells us how well the model is performing: one of such is **perplexity**.

Extrinsic Evaluation Evaluating N-gram models.

Put model A in a task (language identification, speech recognizer, machine translation system...)

Run the task, get an accuracy for A

Put model B in the task, get accuracy for B

Compare the accuracies

Language Identification Task Build a model for each language and compute probability that text is of such language.

$$lang = \arg\max_{l} P_l(text)$$

Difficulty of Extrinsic Evaluation Extrinsic evaluation is time-consuming, can take days to run an experiment. Recent benchmarks like GLUE have become popular due to the effectiveness.
Intrinsic evaluation us an approximation called **perplexity**: it's a poor approximation unless the test data looks just like the training data.

Perplexity The intuition is the notion of surprise: how surprised is the language model when it sees the test set? Where surprise is a measure of "I didn't see that coming". The more surprised is, the lower the probability it assigned to the test set, and the higher the probability the less surprised it is.
So perplexity measures how well a model "fits" the test data. It uses the probability that the model assigns to the test corpus and normalizes for the number of words in the test corpus, taking the inverse.

$$PP(w) = \sqrt[N]{\frac{1}{P(w_1 \dots w_N)}}$$

Measures the weighted average branching factor in predicting the next word (lower is better).
In the chain rule

$$PP(w) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i \mid w_1 \dots w_{i-1})}}$$

And for bigrams

$$PP(w) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i \mid w_{i-1})}}$$

Lower perplexity $\Rightarrow$ better model

0.4 Representation of Words

Word Meaning Definition of **meaning**:

Idea represented by a word, phrase...

Idea that a person wants to express by using words, signs...

Idea expressed in a work of writing, art...

Signifier (symbol) $\Leftrightarrow$ **Signified** (idea or concept) = **denotation**

Linguistic Solution Dictionary or lexical resources provide word definitions as well as synonyms, hypernums, antonyms... example: **Wordnet**.

Problems with lexical resources

Imperfect, sometimes there are errors

Missing new meanings of words, hard to keep up-to-date

Subjective

Require human labor to create and adapt

Hard to compute accurate word similarity

Vector Space Model The **VSM** is a representation for text used in information retrieval. A document is represented by a vector in a n-dimensional space

$$v(d_1) = [t_1, \ldots, t_n]$$

Each dimension corresponds to a separate term.
The VSM considers words as discrete symbols.

One Hot Representation A word occurrence is represented by one-hot vectors, with the vector dimension being the number of words in a vocabulary and 1 in correspondence of the position of the represented word. Useful for representing a document by the sum of the word occurrence vector, and document similarity given by **cosine distance** (angle between vectors).

tf*idf Measure Term frequency: frequency of the word.
Inverse document frequency (idf): given N total documents and df_i = document frequency of word i, meaning the number of documents with word i

$$idf_i = \log \frac{N}{df_i}$$

Classical VSM Vector is all zeroes with idf_t instead of 1. The vector of a document is the sum of the vectors of its terms occurrence vectors.
Doesn't capture similarity between terms.

Problems with Discrete Symbols All vectors are orthogonal, with no notion of similarity. Search engines try to address the issue using WordNet synonyms but it's better to encode the similarity in the vectors themselves.

Intuition Model the meaning of a word by "embedding" it in a vector space. The meaning of a word is a vectors of numbers (vector models are also called **embeddings**), so a **dense vector space**. Contrast: word meaning is represented in many computational linguistic applications by a vocabulary index.

Word Vectors/Embeddings Build dense vector for each word chosen so that it is similar to vectors of words that appear in similar contexts.
Four kinds:

Sparse Vector Representations

1. Mutual-information weighted word co-occurence matrices

Dense Vector Representations

2. Singular Value Decomposition (and Latent Semantic Analysis)
3. Neural Network Inspired models (word2vec, GloVe, fastText...)
4. Brown Clusters

Distributional Hypothesis A word's meaning is given by the words that frequently appear close-by. Old idea but successful just with modern statistical NLP.
When a word w appears in a text, its context is the set of words that appear nearby (within a fixed-size window). Use of the many contexts of w to build a representation of w.

Word Context Matrix Is a $|V| \times |V|$ matrix X that counts the frequencies of co-occurrence of words in a collection of contexts (i.e. text spans of a given length).

Co-Occurrence Matrix Words $\equiv$ Context words. Rows of X capture similarity yet X is still high dimensional and sparse. One row per word with counts of occurrencies of any other word.
We can compute the distance vectors between words, but neighboring words are not semantically related.

0.4.1 Word Embeddings

Dense Representations Project word vectors $v(t)$ into a low dimensional space R^k with $k << |V|$ of continuous space word representations (a.k.a. **embeddings**)

$$Embed : R^{|V|} \to R^k$$

$$Embed(v(t)) = e(t)$$

Desired properties: remaining dimensions represent the most salient features, so the words with syntactic/semantic similarities are grouped close in space.

Collobert Build embeddings and estimate whether the word is in the proper context using a neural network. Positive examples from text, and negative examples made replacing center word with random one. The loss for the training is

$$Loss(\Theta) = \sum_{x \in X} \sum_{w \in W} \max(0, 1 - f_\Theta(x) + f_\Theta(x^{(w)}))$$

with $x^{(w)}$ obtained by replacing the central word of x with a random word.

Word2Vec Framework for learning words, much faster to train. Idea:

Collect a large corpus of text

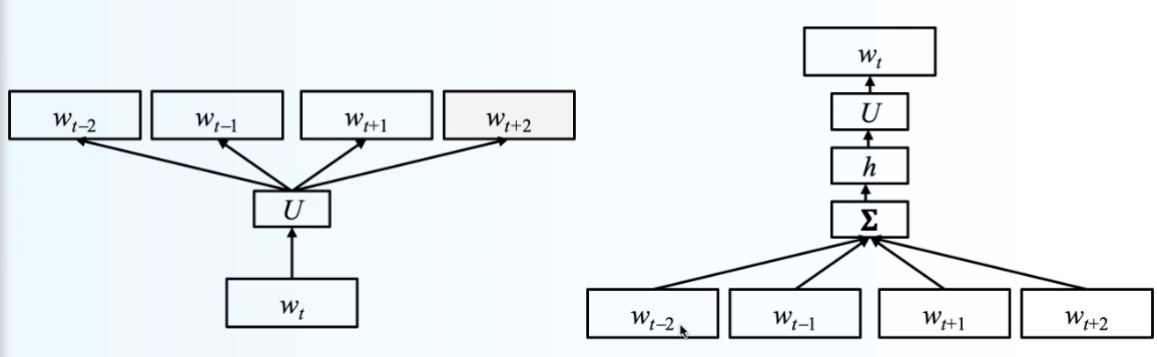
Every word in a fixed vocabulary is represented by a vector

Go through each position t in the text, which has a center word c and context ("outside") words o

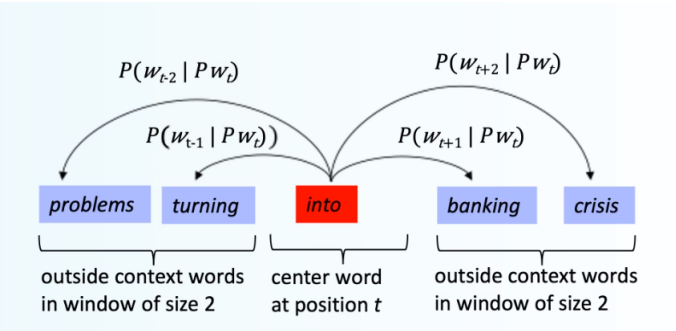
Use the similarity of the word vectors for c and o to calculate the probability of o given c

Keep adjusting word vectors to maximize this probability

Two kinds:



Skip-gram: predict context words within window of size m given the center word w_t



CBoW: predict center word w_t given context words within window of size m

Embeddings are a by-product of the word prediction task. Even though it's a prediction task, the network can be trained on any text (no need for human-labeled data!).
Usual context size is 5 words before and after. Features can be multi-word expressions. Longer windows can capture more semantics and less syntax.
A typical size for h is 200-300.

Skip-Gram

Inputs are one-hot representation of the word

$w \in R^{|Vocabulary|}$ are high-dimensional

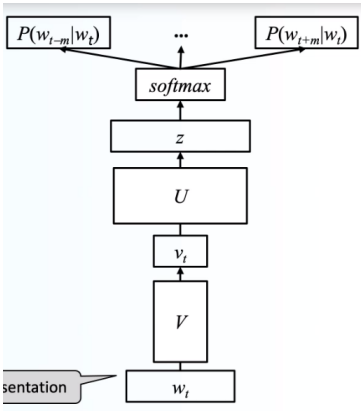
$v \in R^d$ is low dimensional: size of the embedding space d

$V \in R^{|Voc| \times d}$ input word matrix

row t of V is the input vector, representation for **center** word w_t

$U \in R^{d \times |Voc|}$ output matrix

column o of U is the output vector, representation for **context** word w_o



$v_t = w_t V$ embedding of word w_t
$z = v_t U$ z_i is the similarity of w_t with w_i
Softmax converts z to a probability distribution p_i

$$p_i = \frac{e^{z_i}}{\sum_{j \in V} e^{z_j}}$$

Procedure

Lookup the embedded word vector for the center word $v_c = V[c] \in R^n$

Generate score vector $z = v_c U$

Turn the score vector into probabilities $\hat{y} = \text{softmax}(z)$

$\hat{y}_{c-m}, \ldots$ Those are the estimates of the probabilities of observing each context word. These should match the true probabilities, which are

$$y^{c-m}, \ldots, y^{(c-1)}, y^{(c+1)}, \ldots, y^{(c+m)}$$

The training iterates through the whole corpus predicting surrounding words given the center word.

Objective Function For each position $t = 1, \ldots, T$ predict context words within a windows of fixed size m given each center word w_t

$$\text{Likelihood} = L(\Theta) = \prod_{t=1}^{T} \prod_{-m \leq j \leq m,\ j \neq 0} P(w_{t+j} \mid w_t, \Theta)$$

While the objective function $J(\Theta)$ is the average negative log likelihood

$$J(\Theta) = -\frac{1}{T} \log L(\Theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{-m \leq j \leq m,\ j \neq 0} \log(P(w_{t+j} \mid w_t, \Theta) =$$

To compute $P(o \mid c, \Theta)$ we use two vectors per word w: v_w when w center word and u_w when w context word. For a center word c and a context word o:

$$P(o \mid c) = \frac{e^{u_o v_c}}{\sum_{w \in V} e^{u_w v_c}}$$

With the dot product $u \cdot v = \sum_i u_i v_i$: larger product $\Rightarrow$ larger probability. Normalize over entire vocabulary to give probability distribution.
$J(\Theta)$ is a function of all windows in the corpus, potentially billions: too expensive to compute. The solution is the stochastic gradient descent, sampling windows randomly and update after each one.

Softmax

Soft because still assign some probability to smaller x_i

Max because amplifies the probability of largest x_i

Can we really capture the concept represented by a word? Philosophical debate.

Negative Sampling $\log \sum_{j \in F} e^{u_j}$ has lots of terms, costly to compute. The solution is to compute it only on a small sample of negative samples, i.e. $\log \sum_{j \in E} e^{u_j}$ where words E are a few (e.g. 5) and sampled using a biased unigram distribution U computed on training data

$$P(w) = \frac{U(w)^{\frac{3}{4}}}{\sum_{w_j \in V} U(w_j)^{\frac{3}{4}}}$$

CBoW Continuous Bag of Words
Mirror of the skip-gram, where context words are used to predict target words.
h is computed from the average of the embeddings of the input context, z_i is the similarity of h with the words embedding of w_i from U.

Which Embeddings V and U both define embeddigns, which to use? Usually just V. Sometimes average pairs of vectors from V and U into a single one or append one embedding vector after the other, doubling the length.

GloVe Global Vectors for Word Representation. Insight: the ratio of conditional probabilities may capture meaning.

$$J = \sum_{i,j=1}^{V} f(X_{ij}) \dots$$

fastText Similar to CBoW, word embeddings averaged to obtain good sentence representation. Pretrained models.

Co-Occurrence Counts

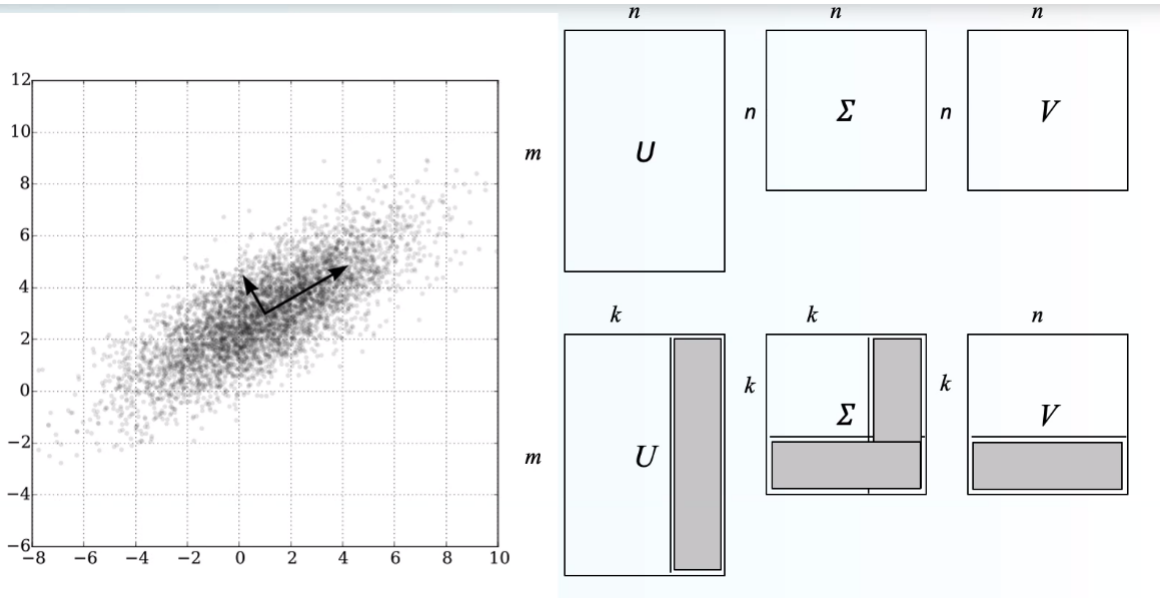
$$P(w_t, w_{t-i}, \dots, w_{t-1}) = \frac{P(w_t, w_{t-i}, \dots, w_{t-1})}{P(w_{t-i}, \dots, w_{t-1})}$$

It's a big matrix, of $|V| \times |V| \simeq 100\text{k} \times 100\text{k} \Rightarrow$ dimensionality reduction: principal component analysis, Hellinger PCA, SVD... trying to reduce to size to 100k×50, 100k×100 or something similar, assigning each word a vector of 50, 100 or similar features.

Weighting Weight the counts using corpus-level statistics to reflect co-occurrence significance: **Pointwise Mutual Information**

$$PMI(w_t, w_{t-i}, \dots, w_{t-1}) = \frac{P(w_t, w_{t-i}, \dots, w_{t-1})}{\log P(w_t) P(w_{t-i}, \dots, w_{t-1})} = \log \frac{\#(w_t, w_{t-i}, \dots, w_{t-1}) \cdot |V|}{\#(w_{t-i}, \dots, w_{t-1}) \#(w_t)}$$

Skip-gram model implicitly factorizes a shifted PMI matrix.
Idea of Singular Value Decomposition:



Which One? No clear winner. Parameters play a relevant role in the outcome of each method. Both SVD and SGNS performed well on most tasks, never underperforming significantly.
SGNS is suggested to be a good baseline: faster to compute and performs well.

Parallel word2vec How to synchronize access to V and U, given multicore CPU to run SGD in parallel? No synchronization is good, because computation is stochastic hence it is approximate anyhow. Parameters are huge: low likelihood of concurrent access to the same memory cell. The effect is a very fast training.

Computing embeddings The training cost of word2vec is linear in the size of the input. The training algorithm works well in parallel, given sparsity of words in contexts and use of negative sampling. It can be halted and restarted at anytime.

Gensim Cython

Fang Uses PyTorch

0.4.2 Evaluation

Polysemy Word vector is a linear combination of its word senses.

$$v_{pike} = \alpha_1 v_{pike_1} + \alpha_2 v_{pike_3} + \alpha_3 v_3$$

with $\alpha_i = \frac{f_i}{f_1+f_2+f_3}$ for the frequencies f_i.
It's intrinsic evaluation.

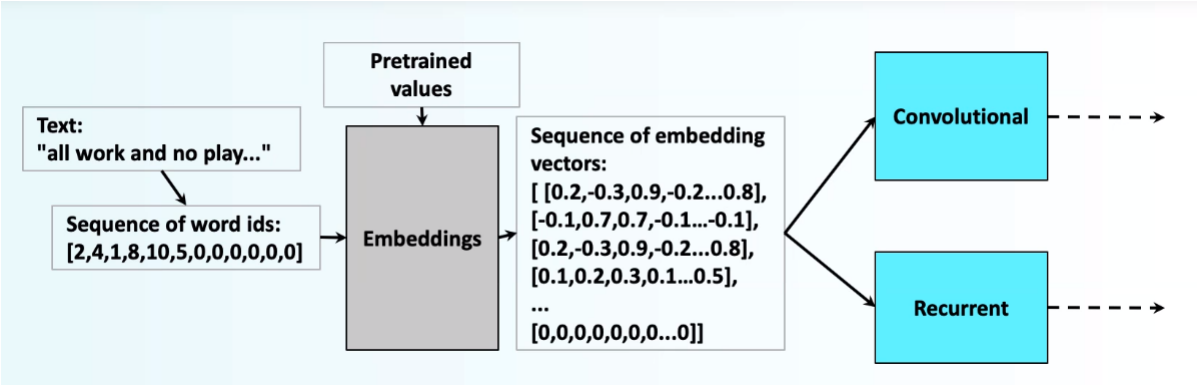
Extrinsic Vector Evaluation The proof of the pudding is in the eating. Test on a task, e.g. NER (Named Entity Recognition)

Embeddings in Neural Networks

An embedding layer is often used as fist layer in a neural network for processing text.
It consists of a matrix W of size $|V| \times d$ where d is the size of the embedding space. W maps words to dense representations.
It is initialized either with random weights or pretrained embeddings. During learning, weights can be:

kept fixed (makes sense only when using pre-trained weights)

updated, to adapt embeddings to the task



Limits of Word Embeddings

Polysemous words

Limited to words (neither multi words nor phrases)

Represent similarity: antinomies often appear similar.
Not good for sentiment analysis or polysemous words. Example:

The movie was **exciting**

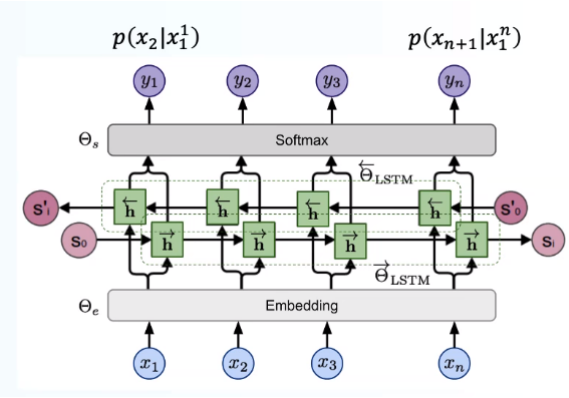
The movie was **boring**

Word Senses and Ambiguity

Sentiment Specific

Context Aware Word Embeddings

ELMo Embeddings from Language Model



Given a sequence of n tokens $(x_1, \ldots, x_n)$, the language model learns to predict the probability of next token given the history

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid x_1^{i-1})$$

The model is trained to minimize the negative log likelihood

$$L = -\sum_{i=1}^{n} \left(\log P(x_i \mid x_1^{i-1}) + \log P(x_i \mid x_{i+1}^{n}) \right)$$

BERT Semi-supervised training on large amounts of text, or supervised training on a specific task with a labeled dataset.

0.5 Text Classification

For example: positive/negative review identification, author identification, spam identification, subject identification...

Definition The classifier $f : D \to C$ with

$d \in D$ input document

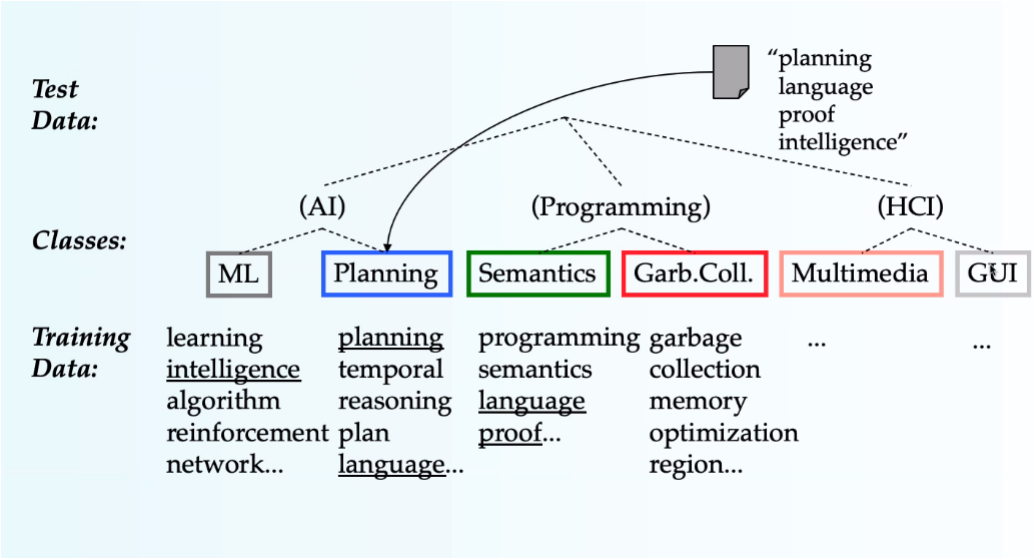
$C = \{c_1, \ldots, c_K\}$ set of classes

$c \in C$ predicted class as output

The learner has

Input: a set of N hand-labeled documents $T = \{(d_1, c_1), \ldots, (d_N, c_N)\}$

Output: a learned classifier $f : D \to C$



Hand-Coded Rules Often very high accuracy, but building and maintaining these rules is expensive. For example: assign category if a document contains a given boolean combination of words (e.g. a blacklist of words for spam classification).

Supervised Machine Learning Input

A document $d \in D$

A fixed set of classes $C = \{c_1, \dots, c_K\}$

A training set of N hand-labeled documents $T = \{(d_1, c_1), \dots, (d_N, c_N)\}$

As output

A learned classifier $\gamma : D \to C$

0.5.1 Naive Bayes

A method based on the Bayes rule, relying on simple document representation (bag of words)

Bag of words representation From a text, we count the frequency of each word.

Bayes Rule Allows to swap the conditioning, useful because sometimes is easier estimating one kind of dependence than the other.

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)}$$

Applied to documents $d \in D$ and classes $c \in C$

$$P(c, d) = P(c \mid d)P(d) = P(d \mid c)P(c)$$

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$

Text classification problem Using a supervised learning method, we want to learn a classifier $\gamma : X \to C$. The supervised learning method is denoted with $\Gamma(T) = \gamma$: it takes the training set T as input and returns the learned classifier γ that can be applied to the test set.

Naive Bayes Classifiers

We represent an instance D based on some attributes $D = (x_1, \dots, x_n)$
Task: classify a new instance D based on a tuple of attribute values into one of the classes $c_j \in C$

$$C_{MAP} = \arg\max_{c_j \in C} P(x_1, \dots, x_n \mid c_j)P(c_j)$$

Naive Bayes Assumption

$P(c_j)$ can be estimated from the frequency of classes in the training examples

$P(x_1, \ldots, x_n \,|\, c_j)$ has $O(|X|^n \cdot |C|)$ parameters and could only be estimated if a very very large number of training examples was available.

The **Naive Bayes Conditional Independence Assumption** is to assume that the probability of observating the conjunction of attributes is equal to the product of the individual probabilities $P(x_i \mid c_j)$. This means that features are independent of each other given the class

$$P(x_1, \ldots, x_n \mid c_j) = P(x_1 \mid c_j) \cdot \ldots \cdot P(x_n \mid c_j)$$

Multinomial Naive Bayes Text Classification

$$C_B = \arg\max_{c_j \in C} P(c_j) \prod_i P(x_i \mid x_j)$$

Still too many possibilities. Assume the classification is independent of the position of the words, and use the same parameters for each position. The result is a **bag of words model** (over tokens, not types).

Learning the Model Maximum likelihood estimate: simply use the frequencies in the data

$$\hat{P}(c_j) = \frac{\text{doccount}(C = c_j)}{\text{doccount}(T)}$$

$$\hat{P}(x_i \mid x_j) = \frac{\text{count}(X_i = x_i, C = c_j)}{\text{count}(C = c_j)}$$

Zero probabilities cannot be conditioned away, no matter the other evidence!

$$l = \arg\max_c \hat{P}(c) \prod_i \hat{P}(x_i \mid c)$$

Smoothing to Avoid Overfitting For example adding 1 to the counts so that it would never be zero (**Laplace**)

$$\hat{P}(x_i \mid c_j) = \frac{\text{count}(X_i = x_i, C = c_j) + 1}{\text{count}(C = c_j) + k}$$

with $k = \#$ values of X_i
Other ways: for example Bayes Unigram Prior

$$\hat{P}(x_{ik} \mid c_j) = \frac{\text{count}(X_i = x_{ik}, C = c_j) + mp_{ij}}{\text{count}(C = c_j) + m}$$

With mp_{ik} overall fraction in data where $X_i = x_{ik}$ and m extent of "smoothing".

Classifying Return the most likely category for a given document

$$C_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_i P(w_i \mid c_j)$$

Preventing Underflow Log space
Multiplying lots of prob can result in floating point underflow. It's better to perform computations by summing logs of probabilities since $\log(xy) = \log x + \log y$
Class with highest final unnormalized log probability is still the most probable

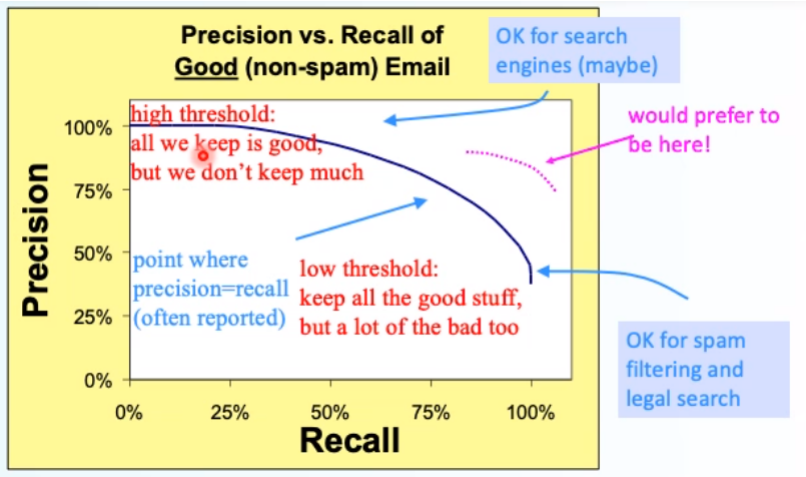
$$C_{NB} = \arg\max_{c_j \in C} \log P(c_j) + \sum_i \log P(x_i \mid c_j)$$

Note: the model is now just a max sum of weights.

Generate We can use naive bayes models to generate text, by using the probabilities of the words.

Naive Bayes and Language Modeling Not the same thing, in naive we want to generalize and can use any sort of features. But if we only use word features and use all the words in a text, then Naive Bayes bears similarity to language modeling.

Evaluating Categorization Must be done on data independent of the training data. Accuracy is $\frac{c}{n}$ where n is the total number of test instancens and c in the number of instances correctly classiefied.



Contingency table

	Correct	Incorrect
Selected	True Positive	False Positive
Not selected	False Negative	True Negative

Micro vs Macro Averaging Macro: performance for each class.
Micro: decision for all classes, compute contingecy table and evaluate

Multiclass Classification More than 2 class, a binary classifier to dinstiguish belongin to a class and *not belonging* to it.

Training Size The more the better, usually.

Violation of Naive Bayes Assumptions Conditional and positional independence.
Naive Bayss is not so naive. Among state of the art algorithms, being robust to irrelevant features (cancel each others).
A good baseline for text classification, but not the best.
Optimal if the independence assumptions hold. Also is very fast, low storage requirements and **online learning algorithm** (incremental training, on new examples).

Example: SpamAssassin Naive Bayes widely used in spam filtering.

0.6 Tokenization

Regular Expressions Formal language for specifying text strings. Letters inside square brackets, or specified ranges, like [] and [A-Z], or negations.
Please refer to online sources. Below is a quick reference table taken from the slides:

Pattern	Matches	Example
[A-Z]	A single uppercase letter	eXample t3xt
[a-z]	A single lowercase letter	eXample t3xt
[0-9]	A single digit	eXample t3xt
[^eX]	Neither 'e' nor 'X'	eXample t3xt
ple	The literal pattern 'ple'	eXample t3xt

Pattern	Matches	Example
colou?r	Optional previous character	color, colour
oo*h!	0 or more of previous character	oh!, ooooh!
oo+h!	1 or more of previous character	ooh!, ooooh!
beg.n	Any single character	begin, beg$n

Tokenization To do before analysis, for information retrieval and extraction, and spell-checking. Three tasks:

1. Segmenting/tokenizing words in running text
2. Normalizing word formats
3. Segmenting sentences in running text

What's a Word? Not easy. Babbling, in spoken language, or "are *cat* and *cats* the same word?".
Terminology:

Lemma: a set of lexical forms having the same stem, major part of speect, and rough word sense. What you would find in a dictionary.
Cat and *cats* = same lemma

Wordform: full inflected surface form.
Cat and *cats* = different wordform

Type/Form: element of the vocabulary

Token: an instance of that type during text

How many words? N tokens and V vocabulary, set of types (of size $|V|$)
$|V| > O(N^{\frac{1}{2}})$
Google N-grams has $N = 1$ trillion and $|V| = 13$ million.

Stanza Tokenizer Toolkit, ternary classifier to distinguish between: normal character, end of token and end of sentence.

Clitics Some languages have composite words: lascia-mi, lascia-me-lo... Splitting clitics is important for parsing, since clitics incorporate relevant syntactic components (e.g. pronouns corresponding to an object of the verb).
Train 4-class tokenizer: normal character, end of token, end of sentence, start of clitic.

Normalization We need to normalize terms (e.g. pick one from U.S.A. and USA). Most commonly we **implicitly define equivalence classes of terms**, e.g. by removing the periods in a term. Another technique is **case folding**, where we reduce all letters to lowercase. But this may be appropriate for information retrieval tasks, while for sentiment analysis this cannot be applied, because there could be difference between e.g. "THAT'S GREAT" and "that's great".
Lemmatization is another technique, where we reduce variant to base term, e.g. "am", "are" and "is" reduced to "be".

Morphology and Stemming A **morpheme** is the smaller meaningful unit that make up words. Two types:

Stems, the core

Affixes, bits and pieces that are attached to the stems to change meaning and grammatical function

Stemming is a technique where we **reduce terms to their roots** before indexing. Basically a crude removal of affixes.

0.7 Classification

1. **Define classes**/categories
2. **Label** text
3. Extract features
4. **Select a classifier**: Naive Bayes Classifiers, Decision Trees, SVMs, Neural Networks...
5. **Train** it
6. Use it to **classify** new examples

The data is easier to handle if it's linearly separable. Naive Bayes models are slightly more general than Decision Trees.

Naive Bayes **Simple model**, can scale easily to millions of training examples, **efficient** and **fast** in training and classification.
A major limitation is the independence assumption, which has two consequences: the linear **ordering of words is ignored** (due to the employing of a bag of words model) and the **words are independent of each other given the class**.
It's an **inappropriate assumption if there are strong conditional dependencies** between the variables. Classifiers may end up "double-counting" the effect of highly correlated features, pushing the classifier closer to a given label than justified. Nonetheless, Naive Bayes models do well in a large number of tasks, because often we are interested in **classification accuracy** rather than an accurate probability estimation.

Decision Trees DTs are **capable to generate understandable rules**, and perform classification without requiring much computation. They **can handle continuous and categorical variables** and provide clear indication of the important features.
But DTs are **prone to errors in classification problems with many classes and small numbers of training examples**, and also they can be **computationally expensive to train**: we need to compare all possible splits, and pruning can be expensive.

Linear vs non-linear algorithms We can find out if data is linearly or non linearly separable **only empirically**. Linear algorithms, when data is linearly separable, are simpler and uses less parameters, but high dimensional data (like for NLP) usually isn't linearly separable. For non linearly separable data, non linear algorithms are more accurate, although more complicated and with more parameters, like kernel methods.

0.7.1 Linear Binary Classification

Data: $\{(x_i, y_i)\}$ for $i = 1, \ldots, n$ with $x \in R^d$ and $y \in \{-1, +1\}$. Question: find a **linear decision boundary** $wx + b$, an **hyperplane**, such that the classification rule associated with it has minimal probability of error.
Classification rule:

$$y = sign(wx + b)$$

In **online fashion**: given one datapoint at the time, update the weights as necessary (to lower the classification error)

Perceptron Compute a weighted sum and output 1 if it exceeds a threshold:

$$z = \sum_i x_i w_i \quad y = \begin{cases} 1 & z \geq \text{threshold} \\ 0 & \text{else} \end{cases}$$

Solves if linearly separable. Basic idea for the **learning rule of a perceptron**: go through all existing data patterns whose label is known, if correct continue. If not, add to the weights a quantity proportional to the product of the input pattern with y (-1 or $+1$)

Multi-Layer Perceptron A MLP architecture has some properties:

No connections within a layer

No direct connections between input and output layers

Fully connected between layers

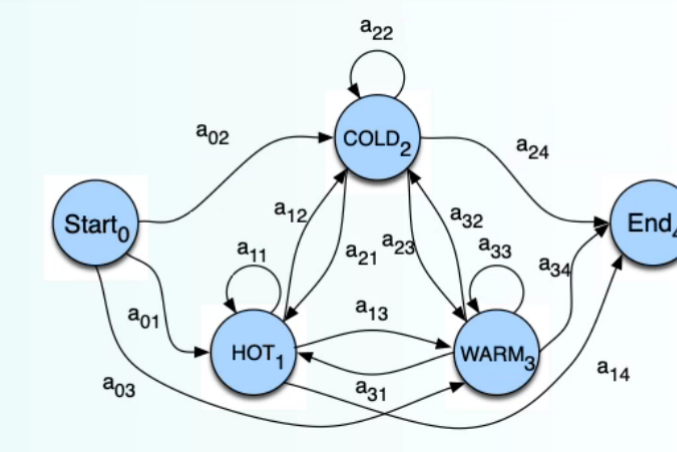
Usually more than 3 layers, and in general the number of input units, output units and hidden layers' units can all differ from each other.

The result of the weighted sum z is passed through an **activation function**, whose output feeds the next layer. Typical examples are σ and tanh.

Universal Approximation Theorem A 2 layer network can approximate any continuous function.
There's no guarantee on the width of each layer, which can be exponentially large.

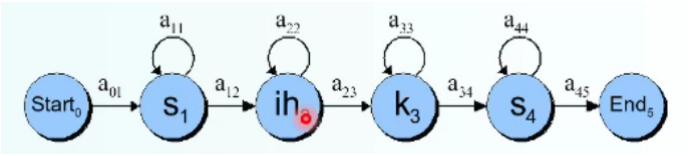
0.7.2 Hidden Markov Models

Markov Chain Stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event.



Hidden Markov Model For the chains, the output symbols are the same as the states. In named-entity or part-of-speech tagging (and speech recognition) the output symbols are **words** and the hidden states are **something else**: POS tags, named-entity tags.
So we need an extension: a **hidden Markov model** is an extension of a Markov chain in which the input symbols are not the same as the states. This means **we don't know which state we're in**.

Example: speech Observed outputs are phones (speech sounds) and hidden states are phonemes (units of sound).
Loopbacks because a phone is circa 100ms but phones are captured every 10ms, so each phone repeats 10 times (simplifying greatly).



A set of N **hidden states** $Q = q_1, \ldots, q_N$

A **transition probability matrix** $A = a_{11}, \ldots, a_{NN}$
Each a_{ij} represents the probability of moving from state i to state j such that $\forall\, i \;\; \sum_{j=1}^{N} a_{ij} = 1$

A sequence of T **observations** $O = o_1, \ldots, o_T$
Each o_i is drawn from a vocabolary $V = v_1, \ldots, v_V$

A sequence of **observation likelihoods**, also called **emission probabilities**, $B = b_i(o_t)$
Each expresses the probability of an observation o being generated from a state i

A special **start state** q_0 and an **end state** q_F that are not associated with observations. This are coupled with transition probabilities $a_{01}, \ldots, a_{0N}$ from the start state and $a_{1F}, \ldots, a_{NF}$ into the end state

Markov Assumption

$$P(q_i \mid q_1, \ldots, q_{i-1} = P(q_i \mid q_{i-1})$$

Output-independence assumption

$$P(o_t \mid O_1^{t-1}, q_1^t) P(o_t \mid q_t)$$

Three basic problems

Evaluation: given the observation sequence $O = (o_1, \ldots, o_T)$ and a HMM model $\Phi = (A, B)$, how to efficiently compute $P(O \mid \Phi)$ (the **probability of the observation sequence given the model**)?

Decoding: given the observation sequence $O = (o_1, \ldots, o_T)$ and an HMM model $\Phi = (A, B)$, how do we choose a corresponding state sequence $Q = (q_1, \ldots, q_T)$ that is **optimal** in some sense (i.e. best explains the observations)?

Learning: how do we adjust the model parameters $\Phi = (A, B)$ (transition and emission probabilities) to maximize $P(O \mid \Phi)$?

Computing the likelihood Given an HMM $\lambda = (A, B)$ and an observation sequence O, determine the likelihood $P(O, \lambda)$.

$$P(O \mid Q) = \prod_{i=1}^{T} P(o_i \mid q_i)$$

$$P(O, Q) = P(O \mid Q) \cdot P(Q) = \prod_{i=1}^{T} P(o_i \mid q_i) \cdot \prod_{i=1}^{n} P(q_i \mid q_{i-1})$$

Forward Algorithm Dynamic programming algorithm: compute the likelihood of the observable sequence by summing over all possible hidden state sequences, but to do this efficiently we fold all the sequences into a single trellis. We compute $P(o_1, \ldots, o_T, q_T = q_F \mid \lambda)$ by recursion.

$\alpha_t(j)$: cell of the forward algorithm trellis that represents the probability of being in state j after seeing the first t observations given the automaton.
Thus the cell expresses the probability

$$\alpha_t(j) = P(o_1, \ldots, o_T, q_T = j \mid \lambda)$$

The recursion is as follows:

1. **Initialization**
$$\alpha_1(j) = a_{0j} b_j(o_1) \quad 1 \leq j \leq N$$
2. **Recursion** (since states 0 and F are non-emitting)
$$\alpha_t(j) = \sum_{i=1}^{N} \alpha_{t-1}(i) a_{ij} b_j(o_t) \quad 1 \leq j \leq N, 1 < t \leq T$$
3. **Termination**
$$P(O \mid \lambda) = \alpha_T(q_F) = \sum_{i=1}^{N} \alpha_T(i) a_{iF}$$

function FORWARD(*observations* of len T, *state-graph* of len N) **returns** *forward-prob*

create a probability matrix *forward*[N+2,T]
for each state s **from** 1 **to** N **do** ; initialization step
  forward[s,1] $\leftarrow a_{0,s} * b_s(o_1)$
for each time step t **from** 2 **to** T **do** ; recursion step
  for each state s **from** 1 **to** N **do**
$$forward[s,t] \leftarrow \sum_{s'=1}^{N} forward[s',t-1] * a_{s',s} * b_s(o_t)$$
$$forward[q_F,T] \leftarrow \sum_{s=1}^{N} forward[s,T] * a_{s,q_F}$$; termination step
return *forward*[q_F, T]

Decoding Given an observation and a HMM, the task of the decoder is to find the best hidden state sequence.
Given the observation sequence $O = (o_1, \ldots, o_T)$, and a HMM $\Phi = (A, B)$, how to choose a corresponding state sequence $Q = (q_1, \ldots, q_T)$ that is optimal in some sense (i.e. best explains the observations)?
One possibility: for each hidden state sequence Q, compute $P(O|Q)$ and pick the highest, but we have N^T possibilities.
Instead: **Viterbi algorithm**, dynamic programming algorithm that uses similar trellis as the Forward algorithm.

Viterbi Algorithm We want to compute the joint probability of the observation sequence together with the best state sequence.

$$\max_{q_0,\dots,q_T} P(q_0,\dots,q_T,o_1,\dots,o_T,q_T=q_F \mid \lambda)$$

$$v_t(j) = \max_{q_0,\dots,q_T} P(q_0,\dots,q_{t-1},o_1,\dots,o_t,q_t=j \mid \lambda)$$

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)a_{ij}b_j(o_t)$$

The recursion is as follows:

1. **Initialization**

$$v_1(j) = a_{0j}b_j(o_1) \quad 1 \le j \le N$$
$$bt_1(j) = 0$$

2. **Recursion** (recall that states 0 and q_F are non-emitting)

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)a_{ij}b_j(o_t) \quad 1 \le j \le N, 1 < t \le T$$

$$bt_t(j) = \arg\max_{i=1}^{N} v_{t-1}(i)a_{ij}b_j(o_t) \quad 1 \le j \le N, 1 < t \le T$$

3. **Termination**
   Best score:

$$P^* = v_t(q_F) = \max_{i=1}^{N} v_T(i) \cdot a_{iF}$$

   Start of backtrace:

$$q_T^* = bt_T(q_F) = \arg\max_{i=1}^{N} v_T(i) \cdot a_{iF}$$

Processes observations from left to right, filling out the trellis. Each cell $v_t(j) = \max_{i=1}^{N} v_{t-1}(i)a_{ij}b_j(o_t)$ is composed of:

$v_{t-1}(j)$ the **previous Viterbi path probability** from the previous time step

a_{ij} the **transition probability** from previous state q_i to current state q_j

$b_j(o_t)$ the **state observation likelihood** of the observation symbol o_t given the current state j

Training a HMM Baum-Welch algorithm (Expectation Maximization), no details.

Part of Speech Tagging

The parts-of-speech, or lexical categories/word classes/lexical tags/POS, are nouns, verbs, adjectives, prepositions... we'll use the term POS the most. Examples:

N, noun

V, verb

ADJ, adjectives

ADV, adverbs

...

For example, "the koala put the keys on the table" → "DET N V..."
But words often have more than one POS: "back" can be ADJ, ADV, N, V. POS tagging problem is determining the POS tag for a particular instance of a word.
We want, out of all sequences of n tags $t_1,\dots,t_n$, the single tag sequence such that $P(t_1,\dots,t_n \mid w_1,\dots,w_n)$ is the highest

$$\hat{t}_1^n = \arg\max_{t_1^n} P(t_1^n \mid w_1^n)$$

We can compute it using the Bayes rule to transform it into a set of other probabilities that are easier to compute.

$$\hat{t}_1^n = \arg\max_{t_1^n} P(w_1^n \mid t_1^n)P(t_1^n)$$

Excluding the denominator because we're taking the maximum. It's composed by likelihood and prior

Likelihood $P(w_1^n \mid t_1^n) \simeq \prod_{i=1}^{n} P(w_i \mid t_i)$ with the naive Bayes assumption

Prior $P(t_1^n) \simeq \prod_{i=1}^{n} p(t_i \mid t_{i-1})$ with the Markov assumption

Two kinds of probabilities

Tag transition probabilities $P(t_i \mid t_{i-1})$
The probabilities that a given tag t_i is preceded by another given tag t_{i-1}.

Word likelihood probabilities $P(w_i \mid t_i)$
The probability that given a tag t_i, it corresponds to the word w_i

To recap, POS tagging can be done in two ways:

As an Hidden Markov Model

$$\hat{t}_1^n \simeq \arg\max_{t_1^n} \prod_{i=1}^{n} \underbrace{P(w_i \mid t_i)}_{\text{Emission}} \cdot \underbrace{P(t_i \mid t_{i-1})}_{\text{Transition}}$$

As a sequence of classifiers

$$\hat{t}_i \simeq \arg\max_{t_i} P(t_i \mid w_{i-k}, \ldots, w_{i+k})$$

Sequence Tagging

For example classifying each token independently using information about the surrounding tokens (sliding window) as input features.
For sequence tagging, sequence models work better: HMMs, MEMMs, conditional random fields, convolutional neural networks...

Discriminative Model Estimate $P(y \mid x)$ in order to predict y directly from x

$$\hat{y} = \arg\max_{y} P(y \mid x)$$

For example: max entropy, logistic regression, Conditional Random Fields, Support Vector Machines, CNNs...

Generative Model Use the Bayes rule to obtain $P(y \mid x)$ and use argmax for classification

$$\hat{y} = \arg\max_{y} P(y)P(x \mid y)$$

For example: naive Bayes, HMMs...

Naive Bayes Compute

$$\hat{c}_j = \arg\max_{j} P(c_j \mid x)$$

using the Bayes rule

$$\hat{c}_j = \arg\max_{j} P(c_j)P(x \mid c_j)$$

Logistic Regression Compute the posterior probability directly

$$P(c_j \mid x) = \frac{e^{w_j x}}{\sum_i e^{w_i x}} = \text{Sofmax}_j(w_j x)$$

$$\hat{c}_j = \arg\max_{j} P(c_j \mid x)$$

In the logistic regression we represent the input x as a vector of features f_i

$$P(c_j \mid x) = \frac{e^{w_j f}}{\sum_i e^{w_i f}} = \text{Sofmax}_j(w_j f)$$

For example:

$$f_1(c, x) = \begin{cases} 1 & \text{if } word_i = \text{"race"} \wedge c = \text{NN} \\ 0 & \text{else} \end{cases}$$

$$f_4(c, x) = \begin{cases} 1 & \text{if is\_lower\_case}(word_i) \wedge c = \text{VB} \\ 0 & \text{else} \end{cases}$$

...

Problems Using Classifiers for Sequence Labeling presents some problems. It's not easy to integrate information from hidden labels on both sides. We **make an hard decision on each token**, when we **should rather choose a global optimum**: the **best labeling for the whole sequence**, and keeping each local decision as just a probability, not a hard decision.
Probabilistic sequence models allow integrating uncertainty over multiple, interdependent classifications and collectively determine the most likely global assignment. Some common approaches are: HMMs (Hidden Markov Models), CRFs (Conditional Random Fields), MEMMs as simplified versions of CRFs, RNNs...

MEMM HMM works in a forward fashion from the tags to the outputs, while a **Maximum Entropy Markov Model works backwards, from the words to the probabilities of the tags**. An MEMM is a discriminative model that extends a standard maximum entropy classifier by assuming that the unknown values to be learned are connected in a Markov chain.

$$P(q_1, \dots, q_N \mid o_1, \dots, o_N) = \prod_t^N P(q_t \mid q_{t-1}, o_t)$$

The probability of a certain label s is modeled in the same way as a maximum entropy classifier

$$P(q \mid q', o) = \frac{e^{w \cdot f(o,q)}}{\sum_{o,q'} e^{w \cdot f(o,q')}} = \text{Softmax}_{o,q}(w \cdot f(o,q))$$

where $f(o,q)$ is a vector of joint (o,q) features and w are the corresponding weights.
Entropy is the **measure of the uncertainty of a distribution**". Given an event x and its probability p_x, the "surprise" is $\log\left(\frac{1}{p_x}\right)$ and **entropy is the expectation of the surprise over** p:

$$H(p) = \mathbb{E}_p\left(\log \frac{1}{p_x}\right) = -\sum_x p_x \log p_x$$

The problem is modeled as such:

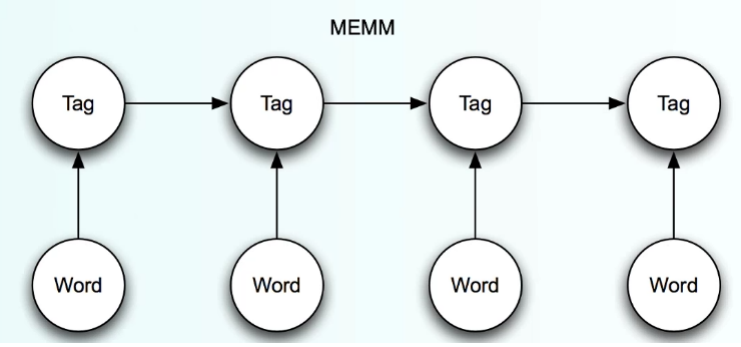
Objective function: $H(p)$

Goal: among all the distributions that satisfy the constraints,choose p^* such that it maximizes $H(p)$

$$p^* = \arg\max_{p \in P} H(p)$$

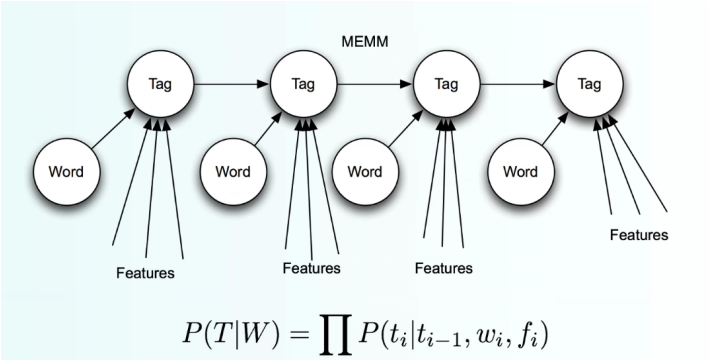
How to represent constraints? We need that the observed feature expectations equals the predicted ones.

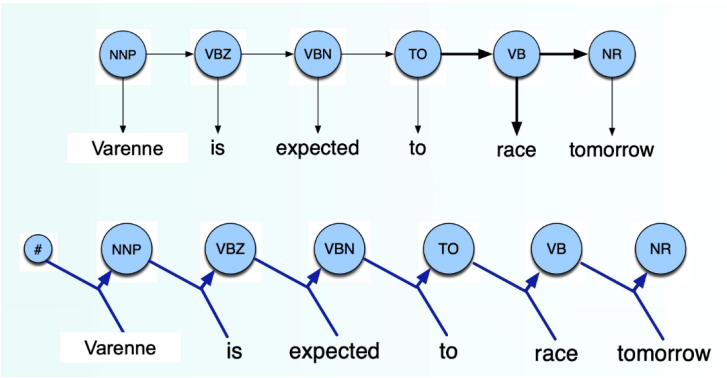
$$\mathbb{E}_p f_j = \mathbb{E}_{\tilde{p}} f_j$$



$$P(T \mid W) = \prod P(t_i \mid t_{i-1}, w_i)$$

We can also add **features** and use them in computing the probabilities.

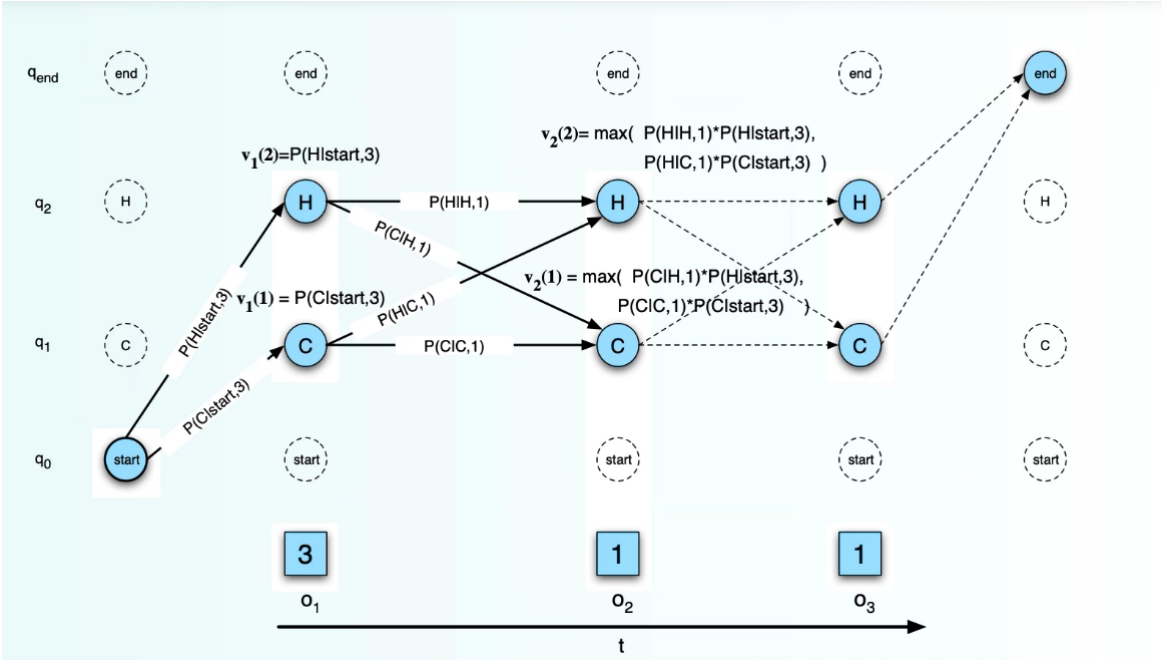




An example of HMM vs MEMM

Viterbi algorithm can be used to select sequence of tags optimal given the whole sentence. In MEMM, decoding via Viterbi is

$$v_t(j) = \max_{i=1} v_{t-1}(i) P(q_j \mid q_i, o_t) \quad \text{for } 1 \le j \le N, 1 < t \le T$$



Named Entity Tagging

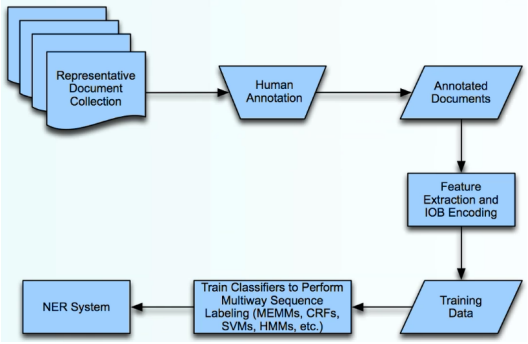
Given a text, find the entities with proper names: person names, city names... the "capitalized things". Typical approach is based on rules, might not be accurate enough. An approach based on ML needs training data, labeling them and using a classifier. Labeling may be easy: annotate each word, but an entity may span more words (name and surname, for example) or be non-continguous, overlapping with other words and perhaps other named entities (examples in biomedical entities).
Typical, named entities systems handle very few categories:

Type	Tag	Sample Categories
People	PER	Individuals, fictional characters, small groups
Organizations	ORG	Companies, agencies, sport teams, parties, religious groups
Location	LOC	Physical extents, mountains, lakes, seas
Geo-political Entities	GPE	Countries, states, provinces, counties
Facility	FAC	Bridges, buildings, airports
Vehicles	VEH	Planes, trains, automobiles

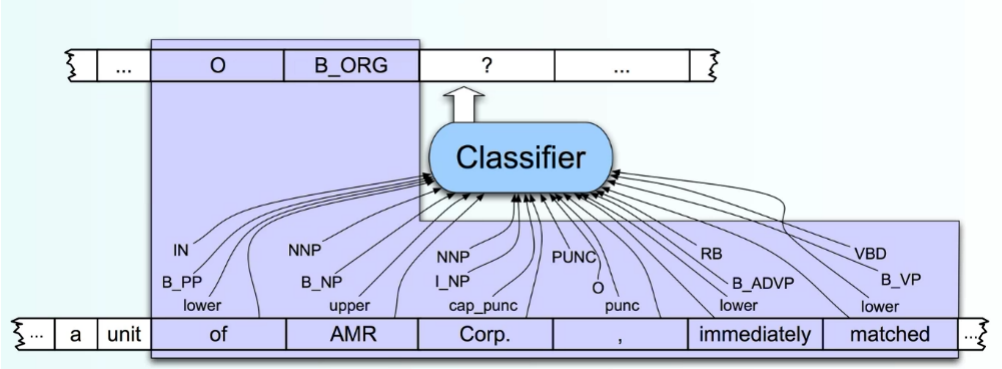
Approaches As with partial parsing and chinking, there are two basic approaches (and hybrids):

Rule-based: patterns to mach things that look like names and environments that classes of names tend to occur in (regular expressions)

ML-based: get annotated data, extract features and train systems to replicate the annotation. Typical approach today



For N classes we have $2N + 1$ tags, with IOB encoding: an I and a B for each tag.



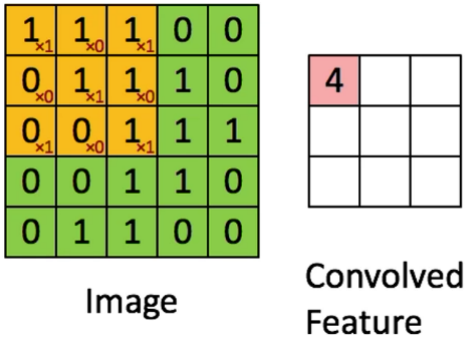
Summary of the approaches.

0.8 Convolutional Neural Networks for NLP

The main idea for the application of CNNs on NLP is to **compute vectors for every possible word subsequence of a certain length**, regardless of whether the phrase is grammatically correct, and group them afterwards. Not very linguistically nor cognitively plausible.
Convolution is classically used to extract features from images

$$(f * g)(n) = \sum_{m=-M}^{M} f(n-m)g(m)$$

Much like a "sliding window" across the data.



A convolutional layer in a NN is composed by a **set of filters**: combines a local selection of input values into an output value, sweeping across all input.
During training each filter specializes into recognizing some kind of relevant combination of features. CNNs work well on stationary features (independent from position). Filters have additional parameters that define:

Padding: the behavior at the start/end of documents

Stride: the size of the sweep step

Dilation: the possible presence of holes in the filter window

Distant Supervision Use the convolutional neural network to further refine the embeddings: word embeddigns from plain text are completely clueless about their sentiment behavior. Collect 10M tweets containing positive emoticons, used as distantly supervised labels to train sentiment-aware embeddings.

Sentiment Specific Word Embeddings The idea is to build sentiment specific word embeddings where we return also the polarity of the word: positive, neutral or negative.
Sentiment Specific Embeddings are learned:

The generic loss function is

$$L_{CW}(x, x^c) = \max(0, 1 - f_\theta(x)_0 + f_\theta(x^c)_0)$$

The SS loss function is

$$L_{SS}(x, x^c) = \max(0, 1 - d_s(x) f_\theta(x)_1 + d_s(x^c) f_\theta(x^c)_1)$$
$$L(x, x^c) = \alpha L_{CW}(x, x^c) + (1 - \alpha) L_{SS}(x, x^c)$$

With gradients

$$\begin{pmatrix} \frac{\partial L}{\partial f_\theta(x)} \\ \frac{\partial L}{\partial f_\theta(x^c)} \end{pmatrix}_0 = \begin{cases} \begin{pmatrix} -1 \\ 1 \end{pmatrix} & \text{if } L_{CW}(x, x^c) > 0 \\ \begin{pmatrix} 0 \\ 0 \end{pmatrix} & \text{else} \end{cases}$$

With x sentence, x^c corrupted sentence obtained by replacing the center word with a random word, $f(x) \in \{0, 1\}^2$ is the function computed by the network and $d_s(x) \in \{1, -1\}$ represents the polarity of x.

Ensemble of Classifiers Fro example, **combine the outputs of two different 2-layer CNNs** with similar architectures but **differing in the choice of certain parameters** (such as the number of convolutional filters).

Sentiment Classification from a Single Neuron A char-level LSTM with 4096 units has been trained on 82M reviews from Amazon, only to predict the next character. After training, one of the units had a very high correlation with sentiment, resulting in **state-of-the-art accuracy when used as a classifier**. The model can also be used to generate text: by setting the value of the sentiment unit, one can control the sentiment of the resulting text.

0.8.1 Regularization

We can use **dropout**: creating a masking vector r of Bernoulli random variables with probability p (hyperparameter) of being 1 and delete features during training

$$h = W(r \otimes z) + b$$

Prevents overfitting. Not used at test time, scaling final vector by probability p. Usually yields an accuracy increase of 2-4%.

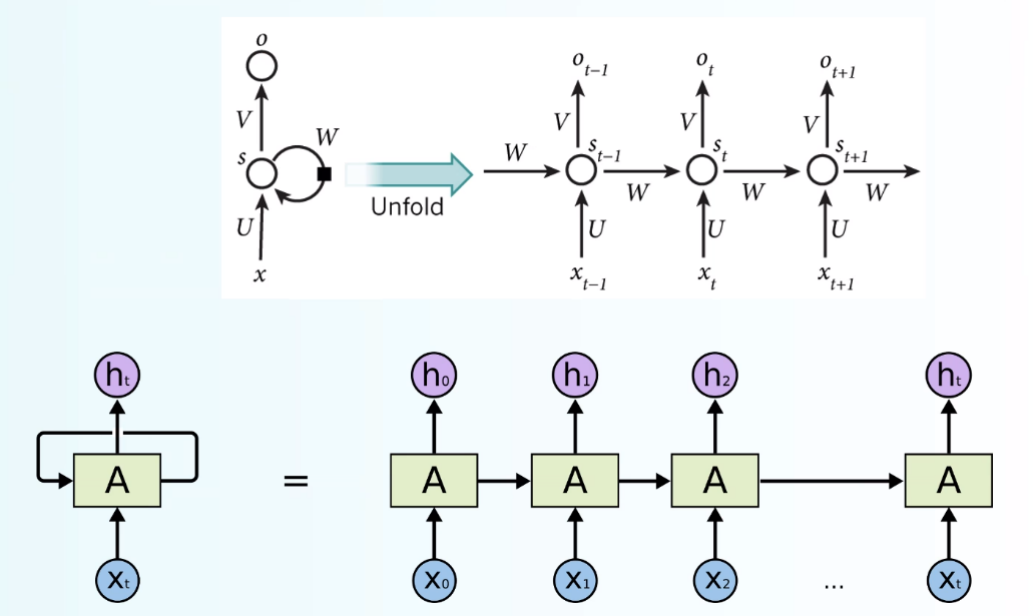
Pitfalls when using word vectors A common problem in training word vectors is how to handle words that are not present in the training dataset. This is solved by using pre-trained word vectors, which are trained on huge amounts of data.
A problem would be the fine-tuning of these pre-trained vectors. If we have a small training set, then we shouldn't fine-tune the word vectors, otherwise then it is better to fine-tune.

0.9 Recurrent Neural Networks

Up until now, whether we grouped words or not each word/group would be handled independently from the others.

Recap A language model assigns to each sentence W a probability $P(W) = P(w_1, \ldots, w_n)$. Alternatively we want to compute $P(w_n \mid w_1, \ldots, w_{n-1})$.
The model that computes either probability is called **Language Model**, and language modeling is the task of estimating a language model.
The Markov assumption is that w_n depends only on the preceding $n-1$ words. n-gram models have sparsity (out-of-vocabulary words and never-seen-prefixes) and storage problems (counts for every n-gram): bigger n makes the sparsity problem worseolt, typically $n < 5$.
Neural Language Models improves over n-gram language models: no sparsity and no need to store all observed n-grams, but still problems: fixed window is too small, never large enough, and no symmetry in the input where each word is still treated independently and multiplied by completely different weights. We need a **neural architecture that can process any length input**.

Recurrent Because they perform the same process for every element where **the output depends on the previous elements**. RNNs have a "memory" which captures information about what has been calculated so far. In theory, RNNs can make use of information in arbitrarily long sequences.



Hidden Units The hidden state s_t represents the memory of the network: it captures information about what happened in all the previous time steps.
The output o_t is computes solely based on the memory at time t.
s_t typically can't capture information from too many time steps ago. Unlike traditional deep networks, which uses different parameters at each layer, a RNN shares the same parameters across all steps (U, V and W above). This reflects the fact that we are performing the same task at each step, just with different inputs, greatly reducing the total number of parameters we need to learn.

Advantages We can process input of any length and model size doesn't increase with longer input. The computation for step t in theory can use information from many steps back.
Weights are shared across timesteps, so representations are shared too.

Disadvantages Recurrent computation is really slow. In practice, is difficult to access information from many steps back.

Simple RNN Language Model

output distribution

$$\hat{y}^{(t)} = softmax(Uh^{(t)} + b_2)$$

Hidden states

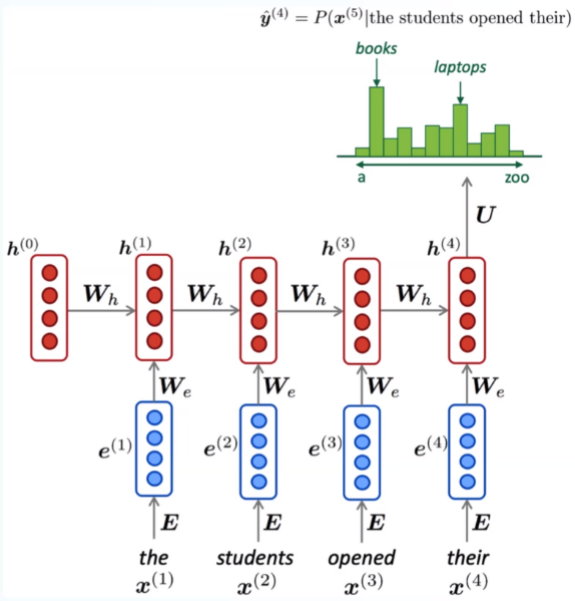
$$h^{(t)} = \sigma(W_h h^{(t-1)} + W_e e^t + b_1)$$

Embeddings

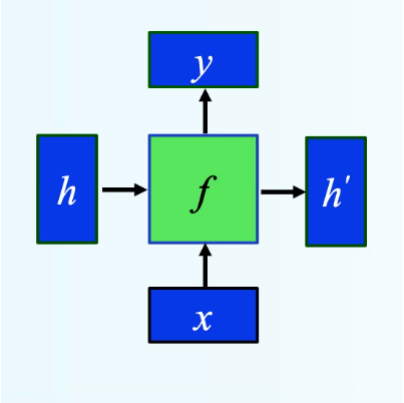
$$e^{(t)} = Ex^{(t)}$$

One-hot vectors

$$x^{(t)} \in \mathbb{R}^{|V|}$$



Vanilla RNN



$$h_t = \sigma\left(Wh_{t-1} + Wx_t + b\right)$$
$$y_t = \sigma\left(Vh_t\right)$$

Notice that y is computed from the current h' only.

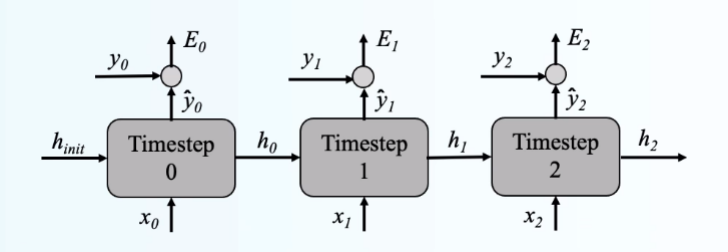
Training Tasks:

for each timestep of the input sequence x we predeict the output y synchronously

for the input sequence x we predict the scalar value of y (e.g. at the end of the sequence)

Main method: **backpropagation**, reliable and controlled convergence, supported by most ML frameworks. Other methods: evolutionary methods, expectation maximization, particle swarm...

Backpropagation through time



Applying the chain rule

$$\frac{\partial h_2}{\partial h_0} = \frac{\partial h_2}{\partial h_1}\frac{\partial h_1}{\partial h_0}$$

For time 2:

$$\frac{\partial E_2}{\partial \Theta} = \sum_{k=0}^{2} \frac{\partial E_2}{\partial \hat{y}_2}\frac{\partial \hat{y}_2}{\partial h_2}\frac{\partial h_2}{\partial h_k}\frac{\partial h_k}{\partial \Theta}$$

Training RNN Language Model Get a big corpus of text and feed into the RNN-LM, computing the output distribution for every step t.
Loss function on step t is cross-exntropy between the predicted probability distribution $\hat{y}$ and the true next word $y^{(t)}$ (one-hot for $x^{(t+1)}$)

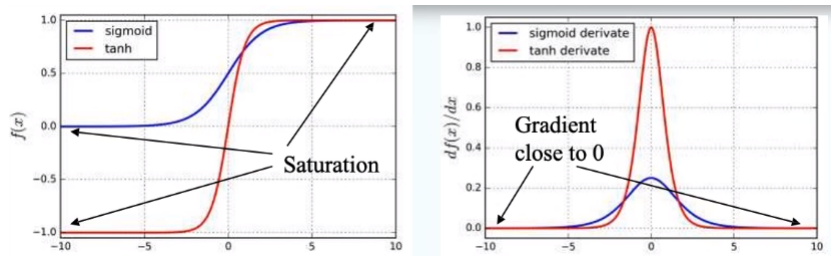
$$J^{(t)}(\Theta) = \text{CrossEntropy}(\hat{y}^{(t)}, y^{(t)}) = -\sum_{w \in V} y_w^{(t)} \log \hat{y}_w^{(t)} = -\log \hat{y}_{x_{t+1}}^{(t)}$$

Average this to get the overall loss for the entire training set

$$J(\Theta) = \frac{1}{T}\sum_{i=1}^{T} J^{(t)}(\Theta) = \frac{1}{T}\sum_{i=1}^{T} -\log \hat{y}_{x_{t+1}}^{(t)}$$

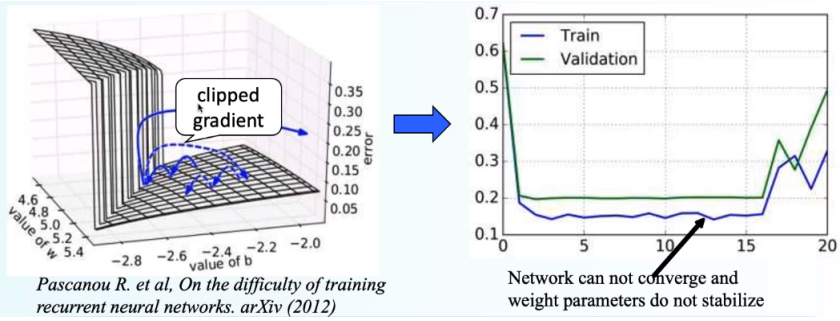
In practice: do this for each sentence and repeat through stochastic gradient descent.

Vanishing Gradients Known problems: the gradients decay exponentially and networks stops learning without updating, making impossible to learn correlations between temporally distant events. A solution is to use ReLU instead of sigmoids.



Smaller weights initialization leads to faster gradient vanishing, and very big initialization make the gradient diverge fast.

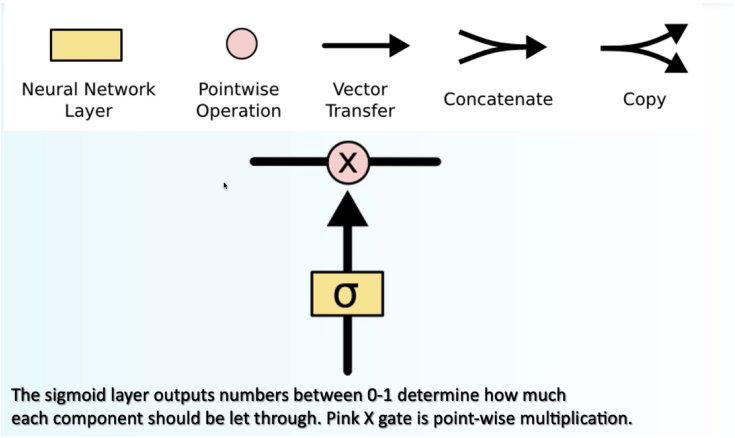
Exploding Gradients The opposite: large increase in the norm, causing NaNs or large fluctuations in cost functions.



Solutions: gradient clipping, reducing learning rates or changing loss function by setting constraints on weights (L1 or L2 norms).

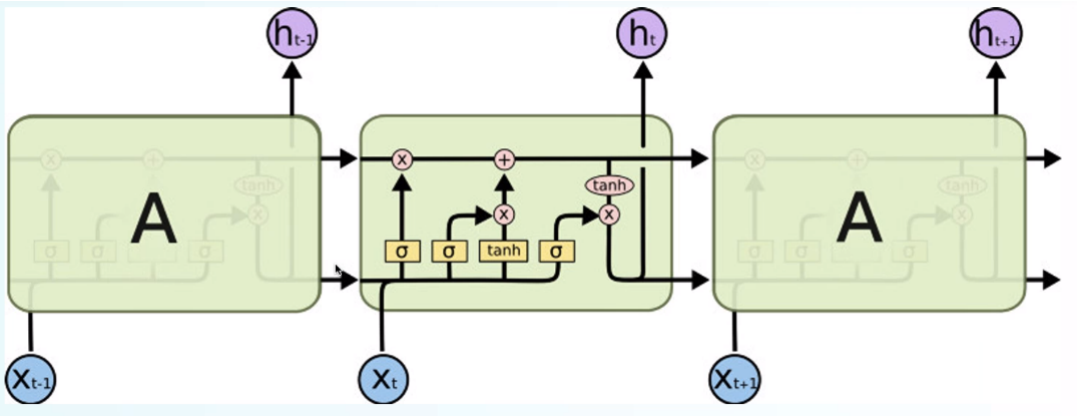
0.9.1 Specializations

Notation



LSTM

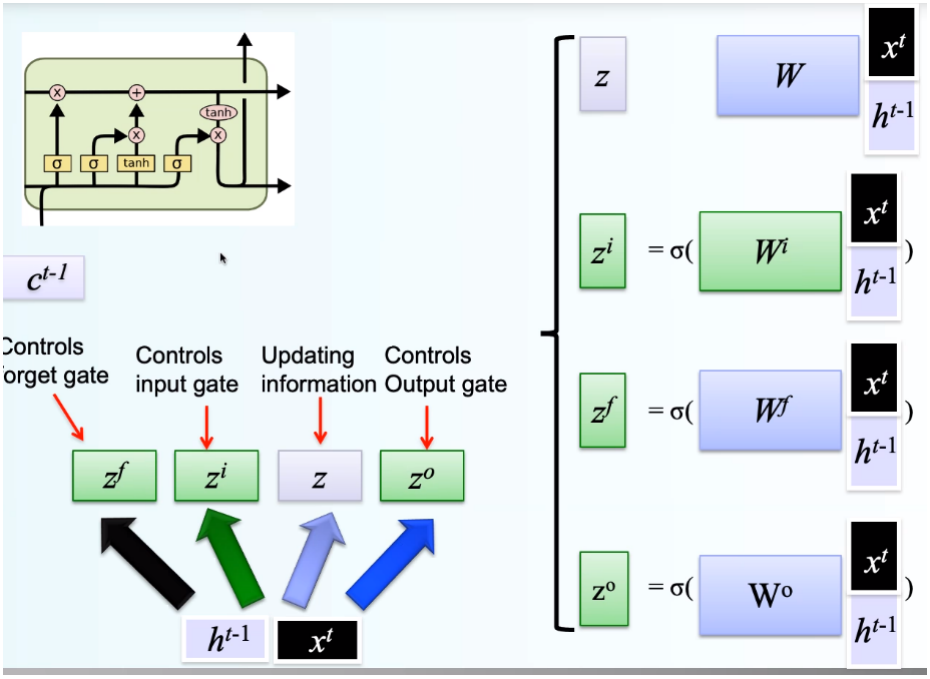
Long Short-Term Memory

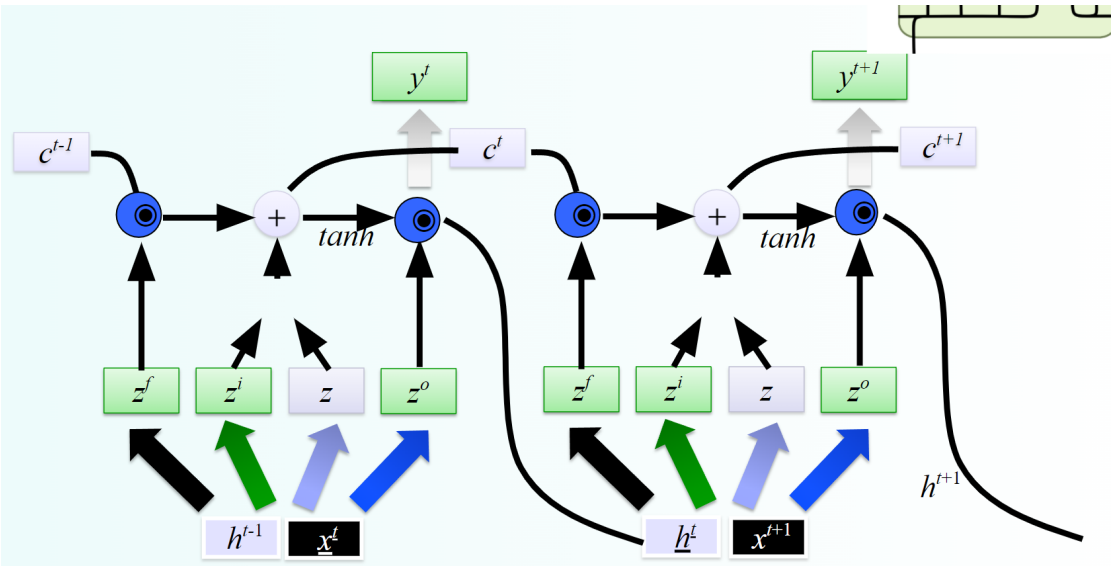


The core idea is this cells state C_t is changed slowly with only minor interactions. Very easy for information to flow unchanged.

$$C_t = f_t C_{t-1} + i_t \hat{C}_t$$

The first sigmoid goes to the **forget gate**, determines how much information goes through.
the second sigmoid is the **input gate** and decides how much input is added in the cell state (so in the next pass).
The **output gate** of the third sigmoid controls what goes in the output.
Why sigmoid or tanh: sigmoid are used as $0/1$ switches, and the vanishing gradients are already handled in the LSTMs.





GRU

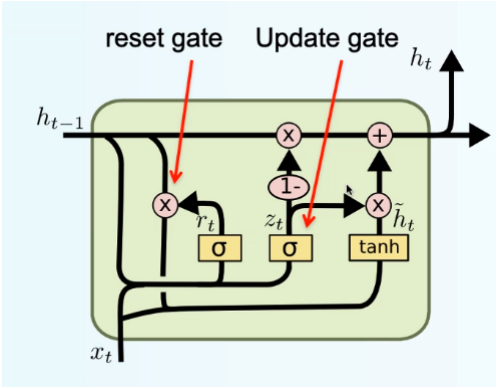
Gated Recurrent Units

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

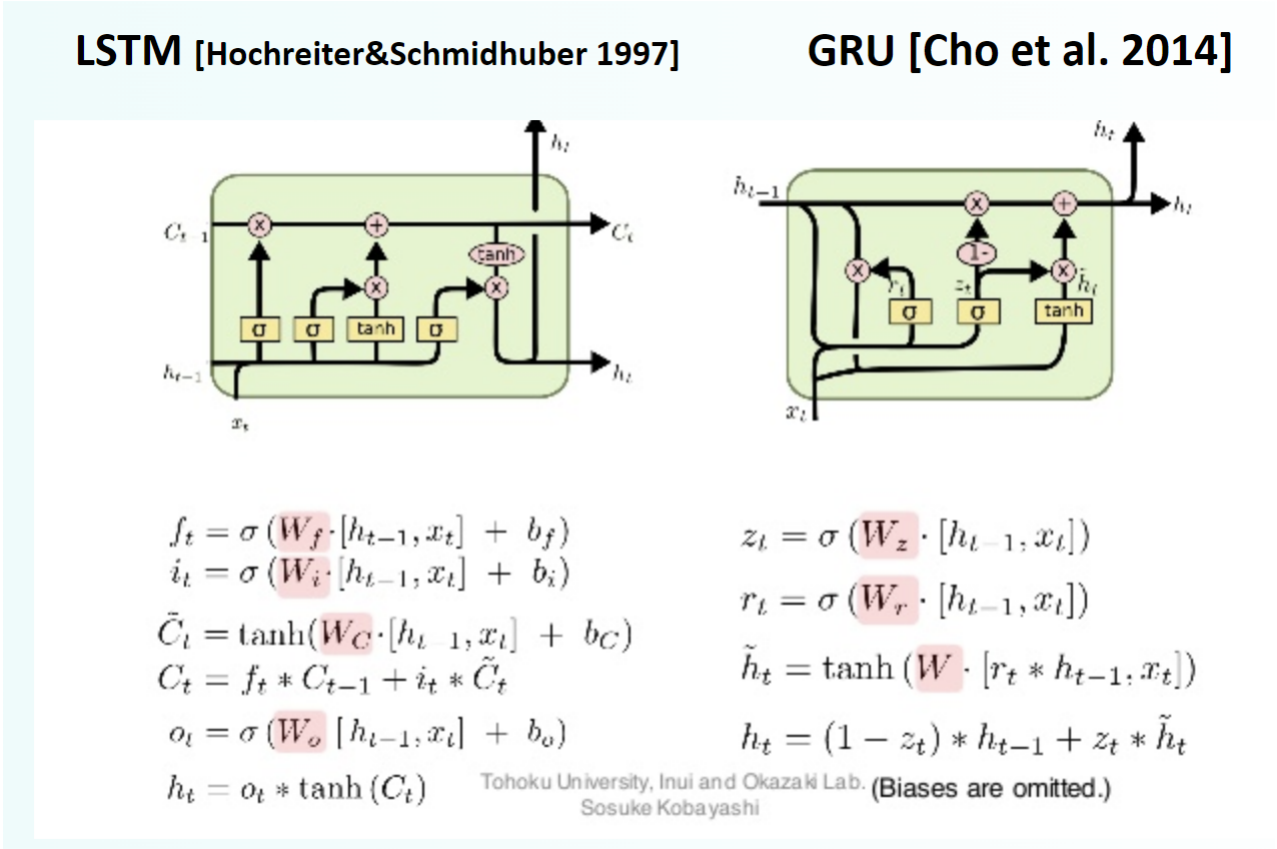
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\hat{h}_t = \tanh(W \cdot [r_t \cdot h_{t-1}, x_t])$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \hat{h}_t$$



Combines forget and input gate into a single update gate, also merging cell state and hidden state. Simpler than LSTM.



0.10 Parsing

Dealing with Text

Bag Of Words representation: enough for classification and information retrieval

N-Grams for language modeling, POS tagging...

Sequences for neural machine translations

But we have nothing that's applicable for information extraction or question answering.

Sentence Structure Recovering the structure is needed to fully understand the language.
Syntax is the way words are arranged together into larger units, and grammar is a formalism used to describe the syntax of a language.
Structural ambiguity: prepositional attachment, coordination scope, verb phrase attachment.

Practical uses of parsing

Relation Extraction: knowledge graph enriched from relation extracted from dependency trees

Semantic Relation

Translation: helps disambiguating sentences

Sentiment Analysis: improved by dependency parsing

Negation: determining the scope of negations

Summarization: detecting relevant parts

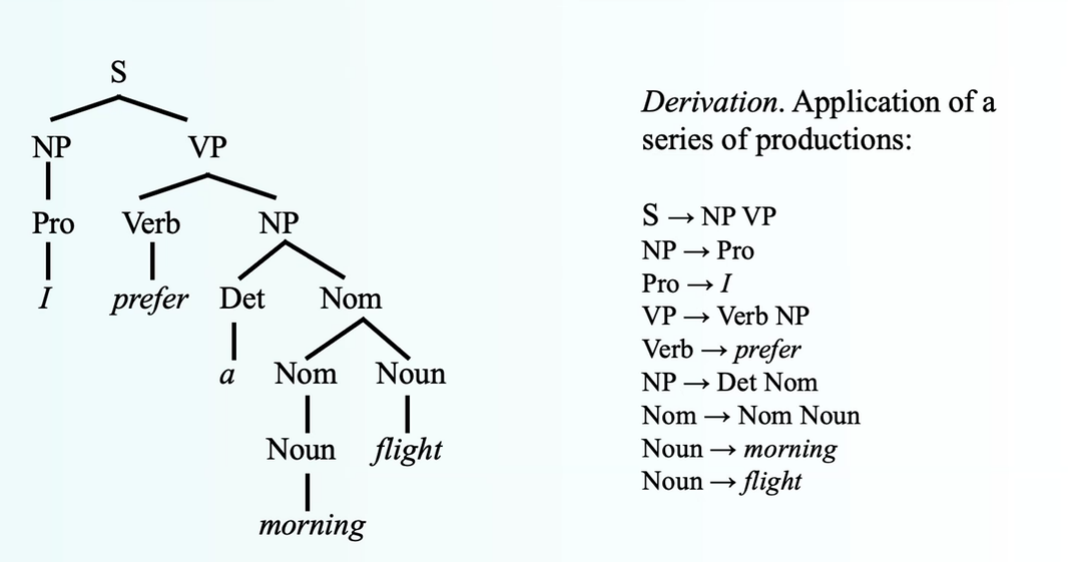
Question Answering

In NLP we've seen information extraction and finding linguistic structure. Can be cast as **learning mapping**: strings to hidden state sequences (POS tagging), strings to strings (translation), strings to trees (**parsing**), strings to relational data structures (information extraction).

0.10.1 Parsing Approaches

Constituency Grammar

AKA phrase structure grammar or **context free grammar**.



Context Free Grammars $G = (N, \Sigma, R, S)$

Set of **non-terminal symbols** N

Set of **terminal symbols** Σ disjoint from N

Set of rules/productions R in the form $A \to \beta$ with A non-terminal, β string of symbols from the infinte set of strings $(\Sigma \cup N)^*$

A designated **start symbol** $S \in N$

The language that G generates, $L(G)$, is the set of every string that can be produced starting from S with the rules in R. Formally:

$$L(G) = \{w \in \Sigma^*, S \to w\}$$

Constituency Parsing Requires phase structure grammar and produces phrase structure parse tree.

Statistical Parsing Three components

GEN is a function from a string to a set of candidate trees.
GEN enumerates a set of candidates for a sentence. It can be a context-free grammar, a finite-state machine, the top N most probable analyses from a probabilistic grammar...

Φ maps a candidate to a feature vector $\in \mathbb{R}^d$ and defines the representation of a candidate.
A **feature** is a function on a structure, e.g. $h(x) =$ the number of times that a particular structure is seen in x.
A **feature vector** is $\phi(x) = \langle h_1(x), \ldots, h_d(x) \rangle$ defined by a set of functions $h_1, \ldots, h_d$

W is a parameter vector $\in \mathbb{R}^d$ and maps a candidate to a real-valued score.

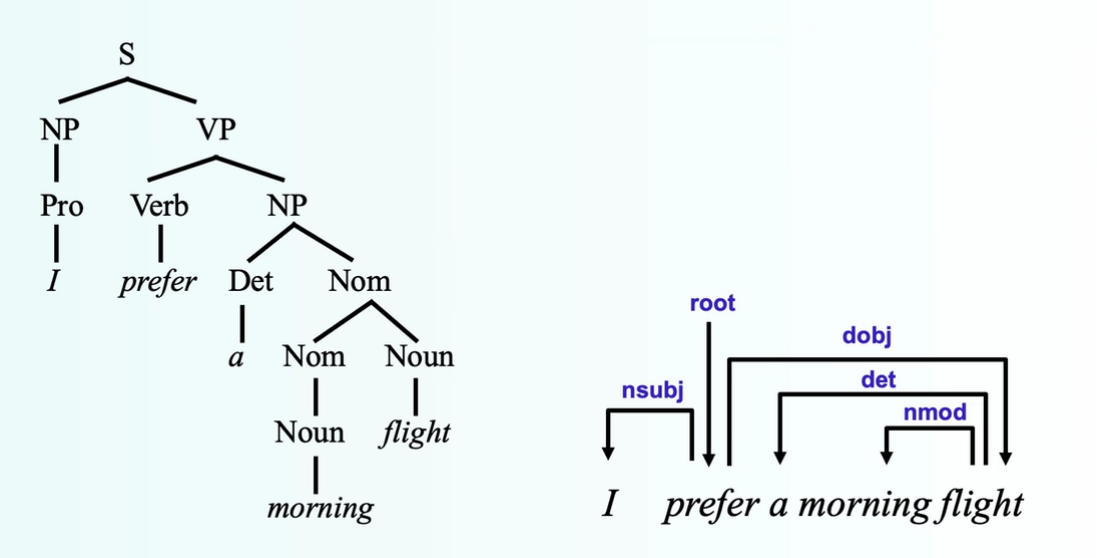
Training by giving a set of sentences X and the set of possible outputs (trees) Y to learn a function $F_W : X \to Y$.
Parsing is choosing the highest scoring tree

$$F_W(x) = \arg \max_{y \in GEN(x)} \Phi(y) \cdot W$$

Dependency Grammar

Dependency Structure Shows which words depend on (modify or are arguments of) which other words. The syntactic structure of a sentence is described only in terms of the words in a sentence and a set of directed binary grammatical relations among the words.

Difference Between Constituency Tree and Dependency Trees



Criteria for a syntactic relation between a head H and a dependent D in a construction C

H determines the syntactic category of C (H can replace C)

H determines the semantic category of C (D specifies H)

H is obligatory and D may be optional

H selects D and determines whether D is obligatory

The form of D depends on H

The linear position of D is specified with reference to H

Annotation Constraints A dependency graph $D = (W, A)$ is a directed rooted tree

D is weakly connected: $i, j \in V \Rightarrow i \leftrightarrow^* j$

D is acyclic: $i \rightarrow j \Rightarrow \neg(j \rightarrow^* i)$

D obeys the **single-head constraint**: $i \rightarrow j \Rightarrow \neg(i' \rightarrow j)\ \forall\, i' \neq i$

The single-head constraints causes problems in handling certain linguistic phenomena.

Data-Driven Dependency Parsing

Graph Based: consider the possible dependency graphs and define a score selecting the best scoring one.

Transition Based: define a transition system that leads to a parse tree while analyzing a sentence one word at a time.

Constraint Satisfaction: edges are deleted that don't satisfy hard constraints.

Transition-Based Shift-Reduce Parsing Traditional statistical parsers are trained directly on the task of tagging a sentence. Instead, a shift-reduce parser **learns the sequence of parse actions required to build the parse tree**. An inductive parser **doesn't require grammar**, while a traditional parser requires a grammar for generating candidate trees.

Parsing as Classification Inductive dependency parsing, based on Shift/Reduce actions: Learn from annotated corpus which action to perform at each step.

Dependency Graph Let $R = \{r_1, \ldots, r_m\}$ the set of dependency types (the tags we'll put on the links).
A dependency graph for a sequence of words $W = w_1, \ldots, w_n$ is a labeled directed graph $D = (W, A)$ where

W is the set of nodes, i.e. the word tokens in the input sequence

A is a set of labeled arcs (w_i, w_j, r) with $w_i, w_j \in W$ and $r \in R$

$\forall\, w_j \in W$ there is at most one arc $(w_i, w_j, r) \in A$

The parser build such a graph. Its state at each time is a triple (S, B, A) where

S is a stack of partially processed tokens

B is a buffer of remaining input tokens

A is the arc relation for the dependency graph

$(h, d, r) \in A$ represent an arc $h - r \to d$ tagged with relation r.

Arc Standard Transitions

$$\text{Shift} \quad \frac{\langle S, n|B, A\rangle}{\langle S|n, B, A\rangle}$$

$$\text{Left-Arc}_r \quad \frac{\langle S|s, n|B, A\rangle}{\langle S, n|B, A \cup \{(n, s, r\}\rangle}$$

$$\text{Right-Arc}_r \quad \frac{\langle S|s, n|B, A\rangle}{\langle S, s|B, A \cup \{(s, n, r)\}\rangle}$$

Parser Algorithm Is fully deterministic, using a trained model to predict the next action, given a representation of the context current state.

```
Input Sentence: (w1, w2, ... , wn)
  S = <>
  B = <w1, w2, ... , wn>
  A = {}
  while B != <> do
        x = getContext(S, B, A)
        y = selectAction(model, x)
        performAction(y, S, B, A)
```

Oracle The gold tree of each sentence can be used to suggest which actions to perform in order to rebuild such gold tree. There can be more than one possible sequence to produce the same parse tree.
An Oracle is an algorithm that given the gold tree for a sentence, produces a proper sequence of actions that a parser may use to obtain that gold tree from the input sentence.
Simplest Oracle: arc standard Oracle, emulates the parser knowing what the outcome should be, returning the correct action at each step. Works but cannot handle certain situation: e.g. non-projectivity situations.

Projectivity An arc $w_i \to w_k$ is projective $\Leftrightarrow \forall j, i < j < k$ or $i > j > k$ we have $w_i \to^* w_j$, so no arc crosses that arc. A dependency tree is projective if and only if every arc is projective.
Intuitively: arcs can be drawn without intersections.

Arc-Standard Algorithm

Doesn't deal with non-projectivity

Every transition sequence produces a projective dependency tree (soundness)

Every projective tree is produces by some transition sequence (completeness)

Fast deterministic linear algorithm: parsing n words requires $2n$ transition.

Arc Eager Transitions

$$\text{Shift} \quad \frac{\langle S, n|B, A\rangle}{\langle S|n, B, A\rangle}$$

$$\text{Left-Arc}_r \quad \frac{\langle S|s, n|B, A\rangle}{\langle S, n|B, A \cup \{(n, s, r\}\rangle}$$

$$\text{Right-Arc}_r \quad \frac{\langle S|s, n|B, A\rangle}{\langle S|s, s|B, A \cup \{(s, n, r)\}\rangle}$$

(Connects without removing, to delay decision and keep words on the stack that might need further connections to children)

$$\text{Reduce} \quad \frac{\langle S|s, B, A\rangle}{\langle S, B, A\rangle}$$

Non-Projective Transitions

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Learning Procedure

Go through each sentence in the treebank and extract the sequence of actions suggested by the oracle.

Emulate the parser and at each parser state extract a context representation of the state, in terms of features.

Provide the features as input and the suggested action as output to the classifier.

CoNLL-X Shared Task Assign labeled dependency structures for a range of languages by means of a fully automatic dependency parser.

Problems with Oracles Only suggest the correct path. If a parser makes mistakes, it finds itself in a state never seen in training and doesn't know how to recover, causing error propagation.

Graph-Based Depencency Parsing

For an input sequence x define a graph $G_x = (V_x, A_x)$ where

$V_x = \{0, 1, \ldots, n\}$

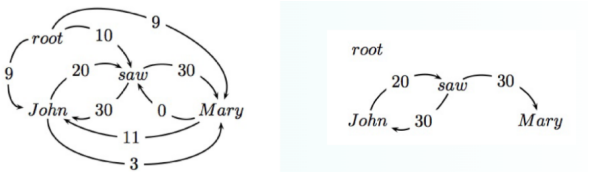
$A_x = \{(i, j, k) \mid i, j \in V \text{ and } k \in L\}$

A key observation is that valid dependency trees for x are **directed spanning trees of** G_x.
A spanning tree is a tree that contains all the vertexes of the original tree and a subset of the arcs, only those needed to connect all the vertexes with one and only one path.
The score of the dependency tree T is given by the score of its arcs:

$$s(T) = \sum_{i,j,k \in T} s(i, j, k)$$

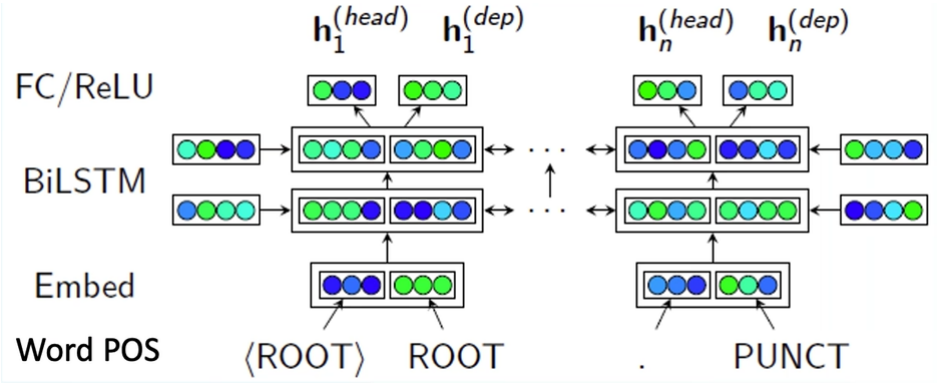
The learning is about the scoring functions $s(i, j, k)$ for each arc (i, j, k). Inference is the search for the maximum spanning tree T of G_x given $s(\,)$.

The basic idea is to choose the arc with the highest score from each node. But the risk is to end up with a graph and not a tree.



Another solution is the **Chu-Liu-Edmonds**: if it's not a tree, identify cycle and contract. Then recalculate arc weights in and out of the cycle. $O(n^2)$ complexity for non-projective trees (much slower than transition-based parsers).

NN Graph-Based Parser Revived graph-based dependency parsing in a neural world, with great results although slower than neural dependency-based parsers.
Bidirectional LSTMs over word/tag embeddings.



Parser Two separate FC ReLU (Fully Connected Rectified Linear Units) layers:

One representing each token as a dependent trying to find its head.

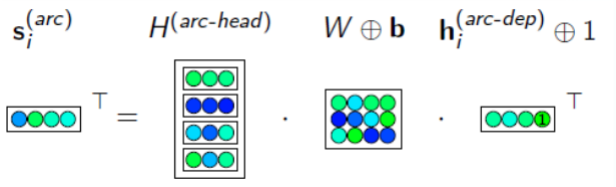
One representing each token as a head trying to find its dependents.

Dependency Relations Two separate FC ReLU layers:

One representing each token as a dependent trying to determine its label.

One representing each token as a head trying to determine its dependents labels.

Self-Attention Biaffine self-attention layer to score a possible heads for each dependent. A $n \times n$ matrix score:

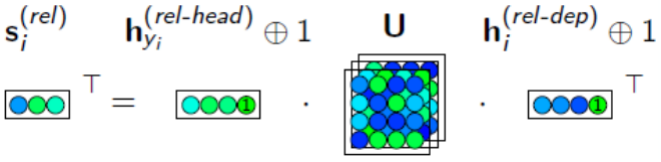


$$s_i = H^{(\text{arc-head})} \cdot \left(W h_i^{(\text{arc-dep})} + b \right)$$

$$H^{(\text{arc-head})} = \left[h_1^{(\text{arc-head})} \ \ldots \ h_n^{(\text{arc-head})} \right]$$

Train with cross-entropy and apply a spanning tree algorithm at inference time.

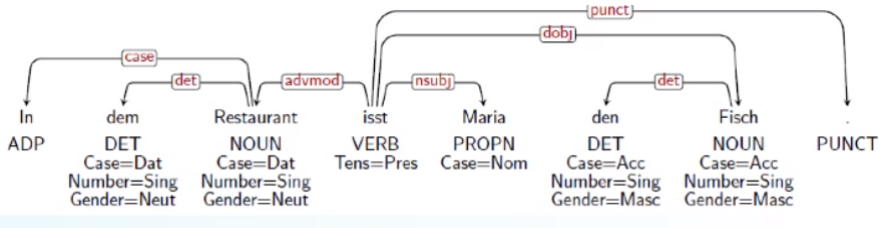
Classifier for Labels Biaffine layer to score possible relations for each best-head/dependent pair, $n \times c$



Train with softmax cross-entropy, added to the loss of the unlabeled parser.

0.11 Universal Dependencies

Treebank annotation schemes vary across languages, hard to compare results across them. Also hard to use to build multilingual.



Goals

Facilitate **consistent notation** of similar constructions across languages

Support **multilingual NLP** and linguistic research

Build on common usage and existing de-facto standards

Complement and not replace language-specific schemes

Community effort where anyone can contribute

Guiding Principles Allow parallelism across languages:

Don't annotate same thing in different ways

Don't make different things look the same

Don't annotate things that are not there

Use a universal pool of categories

Allows language-specific axioms.

Design Principles

Dependency: widely used in practical NLP systems, available in treebanks for many languages.

Lexicalism: the basic annotation units are syntactic words, they have morphological properties and can enter into syntactic relations.

Recoverability: transparent mapping from input text to word segmentation.

Morphological Annotation

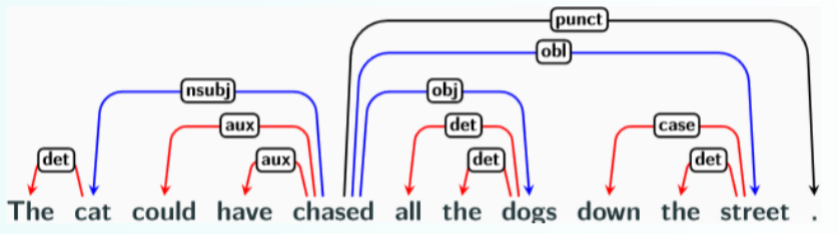
Le La DET Definite=Def Gender=Masc Number=Sing	chat chat NOUN Gender=Masc Number=Sing	chasse chasser VERB Mood=Ind Number=Sing Person=3	les le DET Definite=Def Gender=Masc Number=Sing	chiens chien NOUN Gender=Masc Number=Plur	. . PUNCT

Lemma represent the semantic content of a word

Part-of-Speech tag represent its grammatical class

Morphological Features represent lexical and grammatical properties of the lemma or the specific word form

Syntactic Annotation

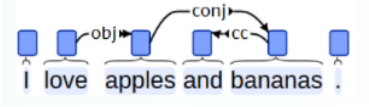


Content Words are used as heads of dependency relations

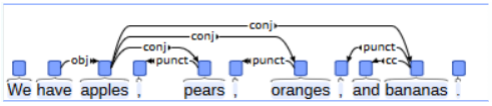
Function Words attach to the content word they modify

Punctuation attach to the head of phrase or clause

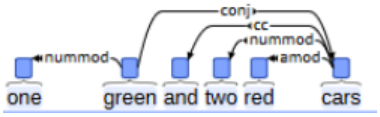
Coordination The first conjunct is the head of all following conjuncts.



Attach coordinating conjunctions and punctuation to the immediately succeeding conjunct.



Except for the right headed constructions.

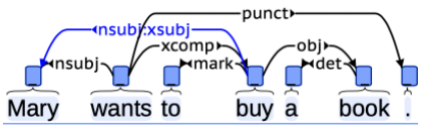


Enhanced Dependencies Making some of the implicit relations between words more explicit, to facilitate relation extractions

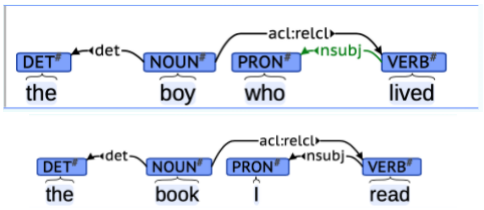
Propagation of conjuncts

Conjoined verb and phrases

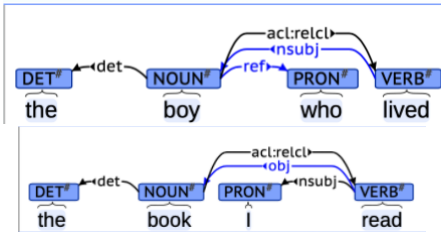
Subject from controller phrases



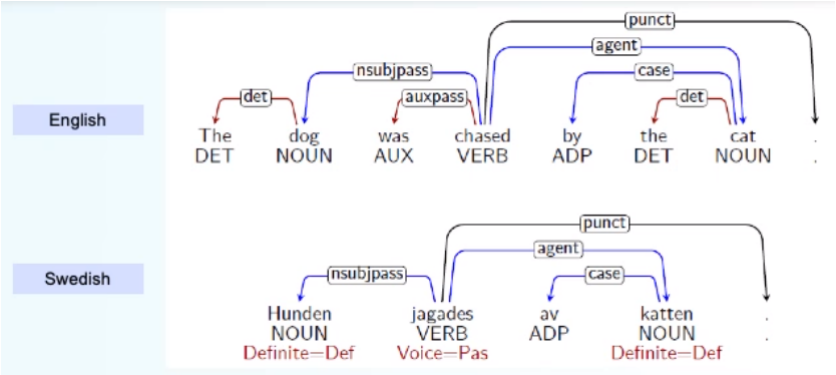
Basic



Enhanced



Dependency Structure The same concept expressed in different languages is represented in similar ways.



Keeping the content words as heads promotes parallelism across languages. The main grammatical relations involving a passive verb, a nominal subject and an oblique agent are the same.

Parsing Can train a parser, also possible to train on multiple languages.

0.12 Machine Translation

Main task that led to the creation of the field, Machine Translation consist in translating a text from one language to another.

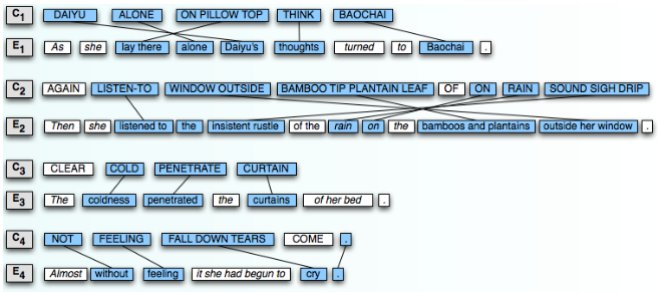
Issues

Sentence **segmentation** (e.g. 4 English sentences to 1 Chinese sentence)

Grammatical differences

Stylistic and **cultural differences**

Alignment



Not just literature! For example, in the European Parliament there are more official languages so all official documents have to be produced in all official languages.

MT Already Good for...

Tasks for which a rough translation is fine: extracting informations, web pages, email...

Tasks for which the MT can be post-edited: MT as first-pass, computer-aided human translation...

Tasks in sublanguage domain where high-quality MT is possible: FAHQT (Fully Automatic High Quality Translation)

MT Not Yet Good Enough for...

Really hard stuff: literature, natural spoken speech...

Really important stuff: medical translations in hospitals, emergency phone calls...

0.12.1 Language Similarities and Divergences

Typology **Some aspects of human language are universal** or near-universal, **others diverge greatly**. **Topology is the** systematic **study of these similarities and divergences**. What are the dimension along which human languages vary?

Morphology

Morpheme: minimal meaningful unit of language.
Word: Morpheme + Morpheme + ...

Stems root plus derivational morphemes
Hope+ing ⇒ **hop**ing

Lemma: also called base form, root, lexeme
Hoping ⇒ Hope
Hopping ⇒ Hop

Affixes:

Prefixes

Suffixes

Infixes

Circumfixes

Morphological Variation In **isolating languages** a single word generally have one morpheme, while in **polysynthetic languages** single words can have many morphemes.
In **agglunative languages** morphemes have clean boundaries, in **fusion languages** a single affix can have many morphemes.

So there's a wide range of synthesis: from vietnamese (isolating) to english to russian to oneida (synthetic).
The other range is fusion: from swahili (agglunative) to russian and oneida (fusion).

Segmentation Variation Not every writing system has word boundaries marked between words, also some languages have very long sentences.
Some languages (**cold languages**) require the hearer to do more "figuring out", while in other (**hot languages**) for example the subject of the sentence is always required.

Lexical Gaps For example, Japanese doesn't have a word for "privacy", or English lacks the word for the Japanese "Oyakoko".

Event-To-Argument Divergences In verb-framed languages we mark the direction of motion on verb, while in satellite-framed languaged we mark the direction in the satellite.

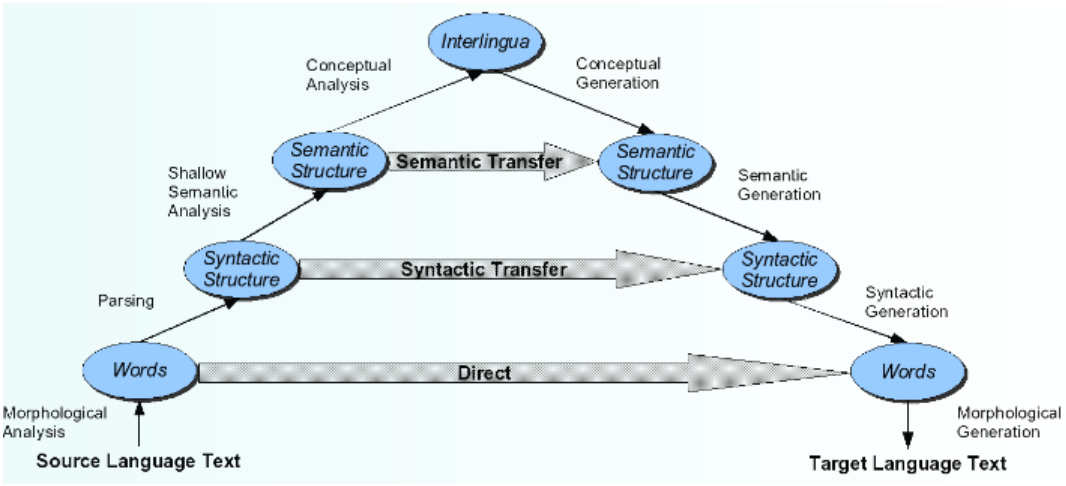
0.12.2 Classical Techniques

Three classical ones:

Direct

Transfer

Interlingua



Direct Translation Proceed word-by-word in the text translating each, without intermediate structures except morphology. Knowledge is in the form of a huge bilingual dictionary and some word-to-word translation information. The dictionary can be more specific for each word, specifying cases and different translation for each case.
The main problem is that we don't "translate" the different syntactic structures and maintain the order of the words of the original language which is often different in the target language.

Pros Fast, simple, cheap, no translation rules hidden in the lexicon.

Cons Unreliable, not powerful, rule proliferation, need major restructuring after lexical subsitution.

Transfer Model We use a set of **transfer rules** that restructure the parse tree. But we need hard to obtain lexical transfer rules. We apply contrastive knowledge: knowledge about the difference between two languages.

Analysis: syntactically parse source language

Transfer: rules to turn this parse into parse tree for target language

Generation: generate target sentence from parse tree

Lexical Transfer Transfer-based systems also need lexical transfer rules, bilingual dictionaries. Can be a list or a word disambiguation system.

Systram Combination of direct and transfer.

Analysis:

Morphological analysis, POS tagging

Chunking of NPs, PPs, phrases

Shallow dependency parsing

Transfer:

Translation of idioms

Word sense disambiguation

Assigning prepositions based on governing verbs

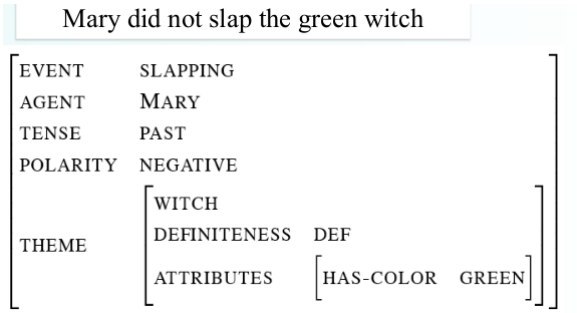
Synthesis:

Apply rich bilingual dictionary
Deal with reordering
Morphological generation

N^2 set of transfer rules, grammar and lexicon full of language-specific stuff, hard to build and maintain.

Interlingua Instead of language-to-language rules, we abstract the meaning of the sentence and translate that.

1. Translate source sentence into meaning representation
2. **Generate** target sentence from meaning



The idea is that some of the MT work that we need to do is part of other NLP tasks: disambiguating eng:book-ita:libro from eng:book-ita:prenotare. So we could have concepts like BOOKVOLUME and PRENOTARE and solve this problem once for each language.

Pros Avoids the N^2 problem, and easier to write rules.

Cons Semantics is hard, useful information lost (because we paraphrase).

0.12.3 Statistical Machine Translation

Example Start from a parallel corpus: a set of sentences in a language and the corresponding sentences in the other language.
Have a sentence to translate into an unknown target sentence into the target language. For each word in the sentence, look for that into the parallel corpus, trying to figure out the translation.

What Makes a Good Translation Two facts to maximize:

Faithfulness or fidelity: **how close is the meaning** of the translation to the meaning of the original.
Even better: does the translation cause the reader to **draw the same inferences** as the original would have?

Fluency or naturalness: **how natural the translation is**, just considering its fluency in the target language.

In SMT, faithfulness and fluency are **formalized**: best-translation $\hat{T}$ of a source sentence S

$$\hat{T} = \arg\max_T \{\text{Fluency}(T) \cdot \text{Faithfulness}(T, S)\}$$

Called the **IBM model**. It's the Bayes rule

$$\hat{T} = \arg\max_T P(T)P(S \mid T)$$

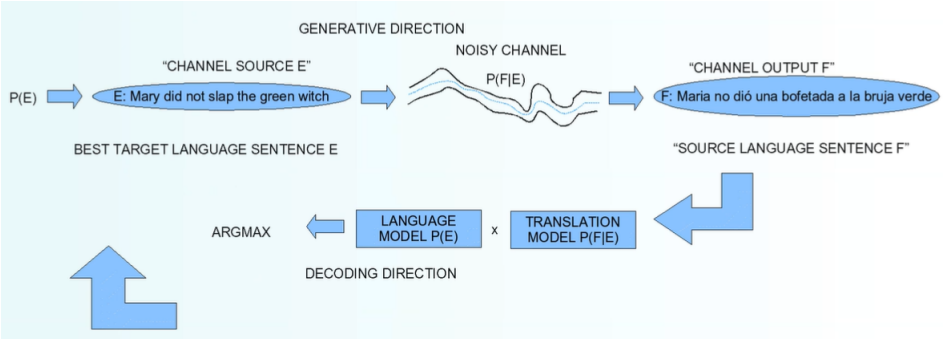
More formally: assume we want to translate from a foreign language sentence F to an English language sentence E

$$F = f_1 \dots f_m$$

We want to find the best English sentence

$$\overline{E} = e_1 \dots e_n = \arg\max_E P(F \mid E)P(E)$$

With $P(E)$ from the language model and $P(F \mid E)$ from the translation model.
Also known as noisy model.



Fluency $P(T)$ How to measure that a sentence is more fluent than another? E.g. "That car was almost crash onto me" is less fluent than "That car almost hit me".
The answer is language models, n-grams! For example, $P(\text{hit} \mid \text{almost}) > P(\text{was} \mid \text{almost})$.
But can use any other more sophisticated model of grammar. Advantage: it's monolingual knowledge.

Faithfulness $P(S \mid T)$ How to quantify? Intuition: degree to which words in one sentence are plausible translations of words in the other sentence. Product of probabilities that each word in target sentence would generate each word in source sentence.
Need to know, for every target language word, the probability of it mapping to every source language word. How to learn this? Parallel texts: lots of times we have two texts that are translations of each other. If we knew which word in Source text mapped to each word in Target text, we could just count.

Sentence Alignment Figuring out which source language sentence maps to which target language sentence.

Word Alignment Figuring out which source language word maps to which target language word.

The faithfulness model $P(S \mid T)$ just models a "bag of words" which words come from e.g. English to Italian.
$P(S \mid T)$ doesn't have to worry about internal facts about target word order, that's the job of $P(T)$.
$P(T)$ can do bag generation: put the following words in order.

Three Problems for Statistical Machine Translation

Language Model: given an English string e, assigns $P(e)$ by a formula such that:

Good English string $\Rightarrow$ high $P(e)$
Random word sequence $\Rightarrow$ low $P(e)$

Can be trained on large, unsupervised mono-lingual corpus for the target language, and could use more sophisticated PCFG language model to caputre long-distance dependencies. Terabytes of web data used to build large 5-gram models.

Translation Model: given a pair of strings $\langle f, e \rangle$, assigns $P(f \mid e)$ by a formula such that:

$\langle f, e \rangle$ look like translations $\Rightarrow$ high $P(f \mid e)$
$\langle f, e \rangle$ don't look like translations $\Rightarrow$ low $P(f \mid e)$

Decoding Algorithm: given a language model, a translation model and a new sentence f, it finds the translation e that maximize $P(e)P(f \mid e)$

0.12.4 Phrase Based Machine Translation

Follows three steps

1. Group words into phrases
2. Translate each phrase
3. Move the phrases around

$P(F \mid E)$ is modeled by translating phrases in E to phrases in F. First segment E into a sequence of phrases $\overline{e}_1, \ldots, \overline{e}_I$, then translate each $\overline{e}_i$ into $\overline{f}_i$ based on **translation probability** $\phi(\overline{f}_i \mid \overline{e}_i)$. Then, reorder translated phrases based on **distortion probability** $d(i)$ for the $i$the phrase.

Translation Probabilities Assuming a phrase aligned parallel corpus is available or constructed that show matching between phrases in E and F. Then compute (MLE) estimate of ϕ based on simple frequency counts

$$\phi(\overline{f}, \overline{e}) = \frac{\text{Count}(\overline{f}, \overline{e})}{\sum_f \text{Count}(f, \overline{e})}$$

Distortion probability The probability that a phrase in position X in the original sentence moves to position Y in the translation.
Distortion is the measure of distance between positions of corresponding phrases in the 2 languages. Distortion of phrase i as the distance between the start of the foreign phrase generated by $\overline{e}_i$ (a_i and the end of the foreign phrase generated bu the previous phrase $\overline{e}_{i-1}$ (b_{i-1}). Typically we assume the probability of a distortion decreases exponentially with the distance of the movement

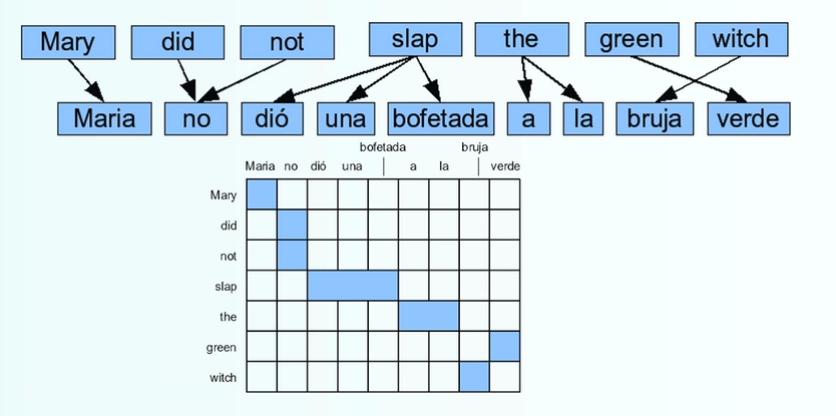
$$d(i) = c\alpha^{|a_i - b_{i-1}|}$$

Set $0 < \alpha < 1$ base on fit to phrase-aligned training data. Then set c to normalize $d(i)$ so that it sums to 1.

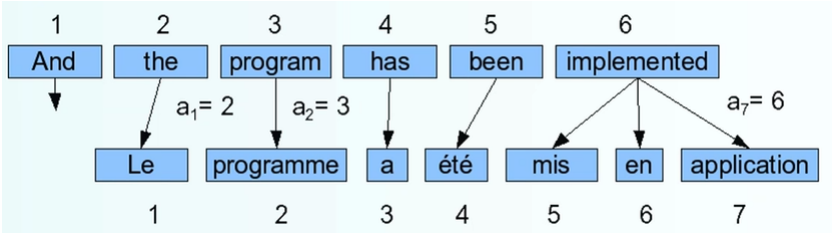
Training $P(F \mid E)$ What we mainly need to train is $\phi(f_j \mid e_i)$
Suppose we had a large bilingual training corpus: a **bitext**. Suppose also to know exactly which phrase in the target language was the tranlsation of which phrase in the source language: **phrase alignment**.
If we had this, we could just count-and-divide

$$\phi(\overline{f}, \overline{e}) = \frac{\text{Count}(\overline{f}, \overline{e})}{\sum_f \text{Count}(f, \overline{e})}$$

But we don't have phrase alignments. We have **word alignments**.



Actually we have more restrictive word alignments. Word alignments are mapping between source and target words in parallel sentence. Restriction: each foreign word come from exactly one source word.



Advantage: represent alignment by the index of the English word that the french word comes from. The above alignment thus is 2,3,4,5,6,6,6.
Spurious words are words in the foreign sentence that does not align with any word in the source language. We assume one to many alignment: each word in F aligns with 1 word in E, with some words in F coming from NULL.

Computing Word Alignments IBM-Model 1. For phrase-based machine translation we need a word-alignment to extract a set of phrases.
A word alignment model gives us $P(F, E)$, and we want this to train our phrase probabilities $\phi(f_j \mid e_j)$ as part of $P(F \mid E)$.
A word-alignment model allows to compute the translation probability $P(F \mid E)$ by summing the probabilities of all possible $(l+1)^m$ "hidden" alignments A between F and E

$$P(F \mid E) = \sum_A P(F, A \mid E)$$

IBM-Model 1 assumes the following simple generative model of producing F from $E = e_1, \ldots, e_l$:

1. Choose length J of F sentence: $F = f_1, \ldots, f_J$
2. Choose a 1 to many alignment $A = a_1, \ldots, a_J$
3. For each position j in F, **generate** a word f_j from the aligned word e_{a_j} in E

Its goal is to find the most probable alignment given a prameterized model

$$\hat{A} = \arg\max_A P(F, A \mid E) = \arg\max_A \prod_{j=1}^{J} t(f_j, e_{a_j})$$

Since translation choice for each position j is independent, the product is maximized by maximizing each term

$$a_j = \arg\max_{0 \le i \le l} t(f_j, e_i) \quad 1 \le j \le l$$

Training Alignment Probabilities

Get a parallel corpus, e.g.: Europarl, Hansards...

Sentence alignment. Intuition: use length in words or chars, together with dynamic programming. Ora a simpler MT model.

Use Expectation Maximization to train word alignments.
We can bootstrap alignment from a sentence-aligned bilingual corpus using the EM algorithm.
$P(A \mid E, F)$ is the probability of the alignment A given a translated pair of sentences E and F

$$P(A \mid E, F) = \frac{P(F, A \mid E)}{P(F \mid E)} = \frac{P(F, A \mid E)}{\sum_{A'} P(F, A' \mid E)}$$

Inherent hidden structure is revealed by EM training.

```
Randomly set model parameters, making sure they represent legal distributions
Until convergence (i.e. parameter no longer change) do:
        E Step: compute the probability of all possible alignments
                of the training data using the current model
        M Step: use these alignment probability estimates to re-estimate values
                for all of the parameters
end
```

Phrase-Based Translation Model

Major components of a phrase-based model:

Phrase translation model $\phi(f \mid e)$

Reordering model $\Omega(f \mid e)$

Language model $P_{LM}(e)$

Bayes rule

$$\arg\max_e P(e \mid f) = \arg\max_e P(f \mid e) P(e) = \arg\max_e \phi(f \mid e) P_{LM}(e) \Omega(f \mid e)$$

Sentences f and e are decomposed into I phrases: $\overline{f}_1^I = \overline{f}_1, \ldots, \overline{f}_I$

$$\phi(f \mid e) = \prod_{i=1}^{I} \phi(\overline{f}_1, \overline{e}_i) d(a_i - b_{i-1})$$

Phrase Alignment Alignment algorithms produce one-to-many word translations, and we know that words do not map one-to-one in translations. Better to map "phrases", sequences of words, to phrases and probabilistically reorder them in translation.
Combine $E \to F$ and $F \to E$ word alignments to produce a phrase alignment.

Decoding

$$P(F \mid E) = \prod_{i=1}^{I} \phi(\overline{f}_i, \overline{e}_i)\, d(a_i - b_{i-1})$$

Look up possible phrase translations: there are many different ways to segment words into phrases and to translate each phrase.
Work by **hypothesis expansion**: start with an empty hypothesis $\langle e, f, p\rangle = \langle , , 1\rangle$ with no english words e, no foreign words covered f and probability $p = 1$. Progressively pick a translation option and create the next hypothesis, until all foreign words are covered. This **explosion of the search space** leads to an exponential number of hypothesis with respect to the sentence length. **Decoding is NP-Complete** and to reduce the search space we can do

Recombination (risk free): different paths may lead to the same partial translation, so combine them by dropping the weaker path (keeping the pointer for lattice generation).
The paths do not have to match completely. A weaker path can be dropped if the last two english words match (which matters for the language model) or if the foreign word coverage vectors match (affects the future path).

Pruning (risky): organize hypothesis in stacks (e.g. by same foreign word covered, or same number of english words produced...) and discard the bad hypothesis:

Histogram pruning: keep the top n hypothesis (e.g. $n = 100$)

Threshold pruning: keep the hypothesis that are at most times the cost of best hypothesis in stack

Evaluation Human subjective evaluation is best but time consuming and expensive. Automated evaluation comparing the output to multiple human reference translations is cheaper and correlates with human judgments.
Better: computer-aided translation evaluation. **Edit cost**: measure the number of changes that a human translator must make to correct the MT output (number of words changed, amount of time taken, number of keystrokes...).

Scores Based on similarity to the reference translations:

BLEU (Bilingual Evaluation Understudy): determine the number of n-grams of various sizes that the MT output shares with the reference translations. Compute a modified precision measure of the n-grams in MT result, averaging n-gram precision over all n-grams up to size N (typically 4) using the geometric mean:

$$p_n = \frac{\sum_{C \in \text{Corpus}} \sum_{n\text{-gram} \in C} \text{Count}_{\text{clip}}(n\text{-gram})}{\sum_{C \in \text{Corpus}} \sum_{n\text{-gram} \in C} \text{Count}(n\text{-gram})}$$

$$p = \sqrt[N]{\prod_{n=1}^{N} p_n}$$

BP (Brevity Penalty): uses a penalty for the translations that are shorter than the reference translation. Define the effective reference length r for each sentence as the length of the reference sentence with the largest number of N-gram matches. With c the candidate sentence length:

$$BP = \begin{cases} 1 & c > r \\ e^{\frac{1-r}{c}} & c \leq r \end{cases}$$

The final BLEU score is

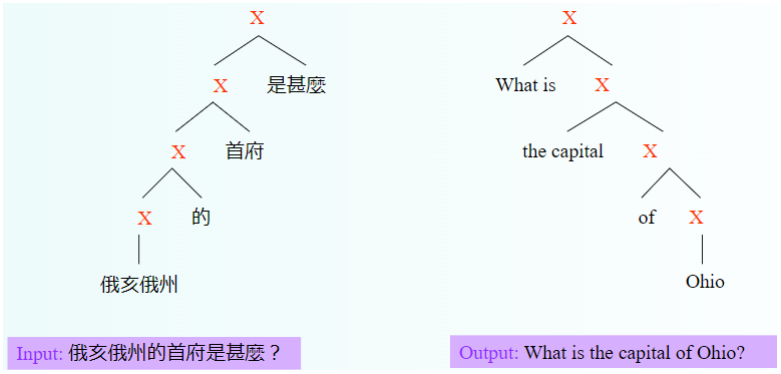
$$BLEU = BP \cdot p$$

Correlates with human evaluation when comparing outputs from different SMT systems, but doesn't correlate with human judgments when comparing SMT systems with manually developed MT or MT with human translations.

0.12.5 Syntax Based Statistical Machine Translation

SMT methods that adopt a syntactic transfer approach. Improved results demonstrated for translating between more distant language pairs (e.g. English-Chinese).

Synchronous Grammar Multiple parse trees in a single derivation. Describes the hierarchical structures of a sentence and its translation, and also the correspondence between their sub-parts.



Synchronous Derivations and Translation Models Need to make a probabilistic version of synchronous grammars to create a translation model for $P(F \mid E)$. Each synchronous production rule is given a weight λ_i, that is used in a maximum-entropy (log linear) model. Parameters are learned to maximize the conditional log-likelihood of the training data

$$\lambda^* = \arg\max_{\lambda} \sum_j \log P_\lambda(f_j \mid e_j)$$

Use of Dependency Parsing Restrict phrases to those corresponding to parse subtrees, and use the parse trees to learn reordering of source language to make it more similar to target language and train a PBMT system on the rearranged parallel corpus.

0.12.6 Minimum Error Rate Training

Also known as MERT. No longer using the noisy channel model, but MERT: train a **logistic regression classifier** to directly minimize the final evaluation metric on the training corpus by using various features of a translation

Language model $P(E)$

Translation model $P(F \mid E)$

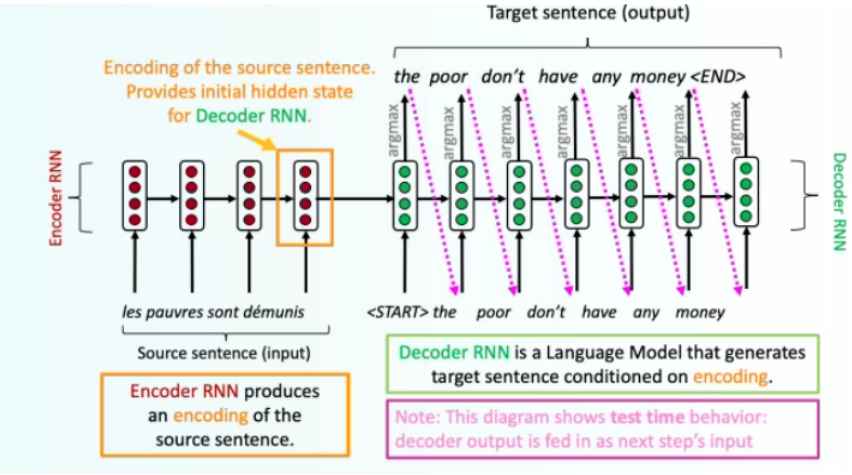
Reverse translation model $P(E \mid F)$

Conclusions Statistical PBMT: phrase table derived by symmetrizing word alignments on a sentence-aligned parallel corpus, statistical phrase translation model $P(F \mid E)$ and language model $P(E)$.
All these combined in a logistic regression classifier trained to minimize error rate.

0.13 Neural Machine Translation

Statistical Machine Translation is a huge research field, but requires the compilation and maintainment of extra resources (for example tables of equivalent phrases), thus lots of human effort to maintain.
In 2014 neural machine translation was introduced with an huge impact on the machine translation field.

NMT Neural Machine Translation is a way of doing MT with a **single neural network**, a sequence-to-sequence (seq2seq) model composed by two RNNs.



A seq2seq model is versatile: a neural network takes an input an produces a neural representation, which is used as input by a second network that produces a sequence as output (**encoder-decoder model**). These models are useful for more than just MT, many natural language processing tasks can be phrased as sequence-to-sequence:

Summarization, long text to short text.

Dialogue, previous utterances to next utterance

Parsing, input text to sequence of parsing symbols

Code generation, natural language to e.g. Python code

The seq2seq model is an example of **conditional language model**:

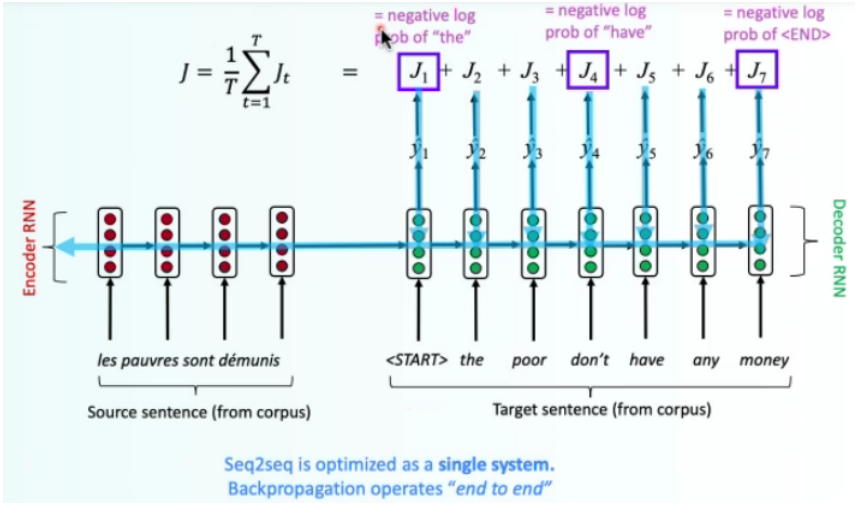
Language model because the decoder is predicting the next word of the target sentence y

Conditional because its predictions are also conditioned on the source sentence x

NMT directly calculates

$$P(y \mid x) = P(y_1 \mid x)P(y_2 \mid y_1, x) \dots P(y_T \mid y_1, \dots, y_{T-1}, x)$$

To train a NMT system, get a big parallel corpus...



Beam Search We showed how to generate (decode) the target sentence by taking the argmax on each step of the decoder. But this is greedy decoding, taking the most probable word on each step, but it has problems e.g. it has no way to undo decisions! A better option would be to use **beam search**, to explore several hypothesis and select the best one. Ideally we want to find a translation y that maximizes

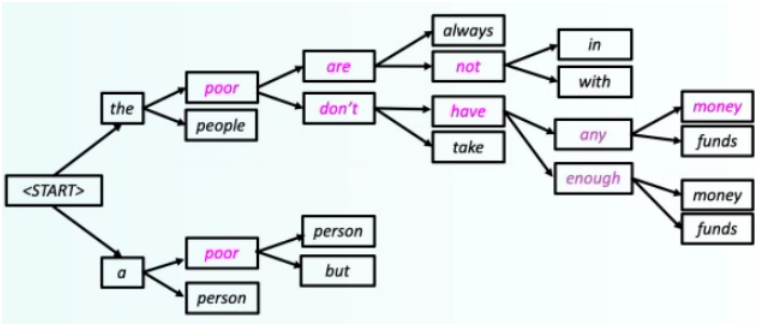
$$P(y \mid x) = \prod_{i=1}^{T} P(y_i \mid y_1, \dots, y_{i-1}, x)$$

We could try computing all possible sequences y: on each step t of the decoder we're tracking V^t possible partial translations with V vocab size. This $O(V^T)$ complexity is too expensive, though, so **beam search**: we keep track of the k most probable partial translations, with k being the beam size ($k \simeq 5, 10$ in practice).
An hypothesis has a score which is its log probability

$$\text{score}(y_1, \dots, y_t) = \sum_{i=1}^{t} \log P_{LM}(y_i \mid y_1, \dots, y_{i-1}, x)$$

Scores are all negative, the higher the better. We search for high-scoring hypothesis, tracking top k on each step. Doesn't guarantee to find the most optimal solution, but it's far more efficient.

Example With $k = 2$



Then we go back finding the complete translations.

Stopping Criterion In greedy decoding, we decode until we find the END token. In beam search, different hypothesis can produce the END tokens on different timesteps: we place it aside and continue exploring other hypothesis. Usually we continue beam search until:

we reach a timestep T, a predefined cut-off, or

we have at least n completed hypothesis, another predefined cut-off

Finishing Up When we have the list of hypothesis, how we select the highest scoring one? Each hypothesis has its score, but longer hypothesis have lower scores so we normalize by length

$$\text{score}(y_1, \dots, y_t) = \frac{1}{t} \sum_{i=1}^{t} \log P_{LM}(y_i \mid y_1, \dots, y_{i-1}, x)$$

Benefits

Better Performance: more fluent, better use of context and of phrase similarities

Single neural network to be optimized end-to-end: no subcomponents to be individually optimized

Requires much less human engineering effort: no feature engineering, same method for all language pairs.

Disadvantages

NMT is less interpretable and hard to debug

NMT is difficult to control: can't easily specify rules or guidelines for translations, also safety concerns

Machine translation is not a solved problem, many difficulties remain:

out-of-vocabulary words

domain mismatch between train and test data

maintaining context over longer texts

failures to accurately capture sentence meaning

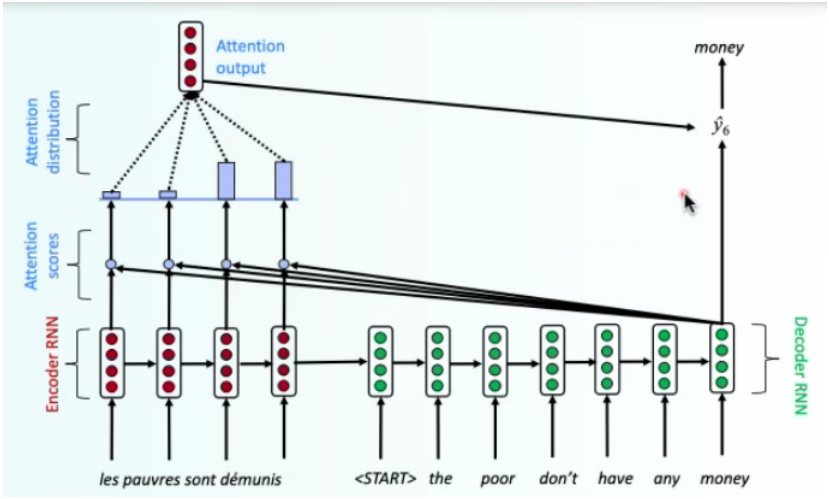
pronouns (or zero pronoun) resolution errors

morphological agreement errors

low-resource language pair

NMT is the flagship task for NLP deep learning: it has pioneered many of the recent innovations of NLP. In 2021 NMT research continues to thrive, researchers have found many improvements to the vanilla seq2seq NMT system presented thus far. But one improvement is so integral that is has become the new vanilla.

Attention Seq2seq has a bottleneck: the encoding needs to capture all the information about the source sentence, it's an **information bottleneck**.
Attention provides a solution to the bottleneck problem. The core idea is: on each step of the decoder, focus on a particular part of the source sequence.



In equations

We have the hidden states in the encoder $h_1, \ldots, h_N \in R^h$

On timestep t we have the decoded hidden state $s_t \in R^h$

We get the attention scores e^t for this step

$$e^t = [s_t^T h_1, \ldots, s_t^T h_N] \in R^N$$

We take the softmax to get the attention distribution for this step (probability distribution that sums to 1)

$$\alpha^t = \text{Softmax}(e^t) \in R^N$$

We use α^t to take a weighted sum of the encoder hidden states to get the attention output a^t

$$a^t = \sum_{i=1}^{N} \alpha_i^t h_i \in R^h$$

Finally, we concatenate the attention output with the decoder hidden state and proceed as in the non-attention seq2seq model

$$[a_t, s_t] \in R^{2h}$$

Attention **significantly improves NMT performance**, solving the bottleneck problem and helping with vanishing gradient problem. Also **provides some interpretability**, and we get alignment for free: we never explicitly trained an alignment system, the network just learned alignment by itself.

Attention Variants We have some values $h_i \in R^h$ and a query $s \in R^h$. Attention involves:

Computing the attention scores $e \in R^N$

Taking softmax to get a attention distribution

$$\alpha = \text{Softmax}(e) \in R^N J$$

Using α to take the weighted sum of values

$$\alpha = \sum_{i=1}^{N} \alpha_i h_i \in R^h$$

Thus obtaining the **attention output** α (sometimes called the **context vector**)

We've seen it in translation, but this can be applied to other NLP tasks. It has becomes a general deep learning technique as well.
A more general definition of attention is: given a set of vector values, and a vector query, attention is a technique to compute a weighted sum of the values dependent on the query. We sometimes say that the query *attends to* the values. E.g. in the seq2seq + attention model, each decoder hidden state (query) *attends to* all the encoder hidden states (values).
Attention is all you need. Self-attention helps to contextualize words: a limit on word embeddings was that each word had a single vector, with attention we can introduce into the representation the context into which they appears, allowing to observe other words.

0.13.1 Self-Attention

Sequence to sequence models with attention are quite effective in transduction tasks, but their sequential nature limits parallelism. The **transformer** transduction model relies entirely on self-attention to compute representations of its input and output: it doesn't use sequence aligned RNNs nor convolutions.
As a result, training costs are reduced by 1-2 orders of magnitude.

So we want **parallelization** but RNNs are inherently sequential. They also generally need attention mechanism to deal with long range dependencies: path length between states grows with distance otherwise. We may be able to just use attention and skip the need for the RNN.

Attention Given a set of vector values and a vector query, attention is a technique to compute a weighted sum of the values dependent on the query.
The intuition is the following: the weighted sum is a selective summary of the information contained in the values, where the query determines which values to focus on. Attention is a way to obtain a fixed-size representation of an arbitrary set of representations (the values), dependent on some other representation (the query).

The generic attention, as we have seen before: we have some **values** $v_1, \dots, v_N \in R^{d_1}$, some **keys** $k_1, \dots, k_N \in R^{d_1}$ and a **query** $s \in R^{d_2}$

Compute the **attention scores** $e \in R^N$

Taking softmax to get the **attention distribution** $\alpha = \text{Softmax}(e) \in R^N$

Using the attention distribution to take the weighted sum of values

$$a = \sum_{i=1}^{N} \alpha_i v_i \in R^{d_1}$$

Thus obtaining the **attention output** or context vector a

There are variants, several ways to compute $e \in R^{d_1}$:

Basic dot-product attention $e_i = s^T k_i \in R$
This assumes $d_1 = d_2$, and is the version used in NMT

Multiplicative attention $e_i = s^T W k_i \in R$
Where $W \in R^{d_1 \times d_2}$ is a weight matrix

Additive attention $e_i = w^T \tanh(W_1 k_1 + W_2 s) \in R$
Where $W_1 \in R^{d_3 \times d_1}$, $W_2 \in R^{d_3 \times d_2}$ are weight matrices and $w \in R^{d_3}$ is a weight vector.
d_3 is the attention dimensionality, hyperparameter.

Issues with Recurrent Models

O(sequence length) steps for distant word pairs to interact. This means: hard to learn long-distance dependencies (because gradient problems!) and linear order of words "baked in" (and we already know that linear order isn't the right way to think about sentences

Non-parallelizable

What can we use instead of recurrence?

Word Windows Word window models aggregate local contexts (also known as 1D convolution). Stacking window layers allow interaction between farther words. The maximum interaction distance is $\frac{\text{sequence length}}{\text{window size}}$

Attention Attention treats each word's representation as a query to access and incorporates information from a set of values. We saw attention from decoder to encoder, let's see attention withing a single sentence. The maximum interaction distance becomes O(1) since all words interact at every layer!

Self-Attention We can think of attention as an approximated hashtable:

To look up a value we compare a query against keys in the table

In a hashtable: each query (hash) maps to exactly one key-value pair

In (self-)attention: each query matches each key to varying degrees. We return a sum of values weighted by the query-key match.

Given the **queries** $q_1, \ldots, q_T \in R^d$, the **keys** $k_1, \ldots, k_T \in R^d$ and the **values** $v_1, \ldots, v_T \in R^d$ (but in practice the number of queries can differ from the number of keys and values), in self-attention **the queries, keys and values are drawn from the same source**. E.g.: if the output of the previous layer is $x_1, \ldots, x_T$ (one vector per word), we could use $v_i = k_i = q_i = x_i$ (same vector for all of them).
The dot product self-attention operation is:

Compute key-query quantities

$$e_{ij} = q_i^T k_j k$$

Compute attention weights from affinities

$$\alpha_{ij} = \frac{e^{e_{ij}}}{\sum_k e^{e_{ik}}}$$

Compute outputs as weighted sum of values

$$\text{Output}_i = \sum_j \alpha_{ij} v_j$$

Vector Notation

With embeddings stacked in X, compute queries, keys and values: $Q = XW^Q, K = XW^K, V = XW^V$

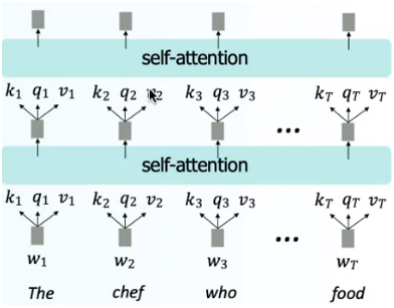
Compute attention scores between queries and keys $E = QK^T$

Take the softmax to normalize attention scores $A = \text{Softmax}(E)$

Take a weighted sum of values Output $= AV$

$$\text{Output} = \text{Softmax}(QK^T)V$$

Self-Attention as a NLP Building Block



This shows a stack of self-attention blocks like we might stack LSTM layers. Self-attention though cannot be a drop-in replacement for recurrence, for it has few issues.

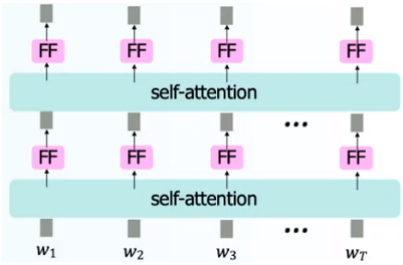
No Notion of Order Self-attention is an operation on sets, meaning it has no inherent notion of order. Self-attention doesn't know the order of its inputs.
We need to encode the order of the sentence in our keys, queries and values. Consider representing each sequence index as a vector: $p_i \in R^d$, for $i \in \{1, \dots, T\}$ are position vectors. It's easy to incorporate this info into our self-attention block: just add the p_i into our inputs. With $\tilde{v}_i, \tilde{q}_i, \tilde{k}_i$ our old values, queries and keys

$$v_i = \tilde{v}_i + p_i$$

$$q_i = \tilde{q}_i + p_i$$
$$k_i = \tilde{k}_i + p_i$$

The p_i can be **sinusoidal position representations**: concatenate sinusoidal functions of varying periods. Periodicity indicates that maybe an "absolute position" isn't important, but it's not learnable. So the p_i can be all learnable: learn a matrix $p \in R^{d \times T}$ and the p_is are columns of that matrix. It's flexible, because each position gets to be learned to fit the data, but can't be used to extrapolate indexes outside $1, \dots, T$.

Adding Non-Linearities Therea re no elementwise nonlinearieis in self-attention, so stacking more self-attention layers just re-averages value records. A simple fix: we add feed-forward network to post process each output vector:



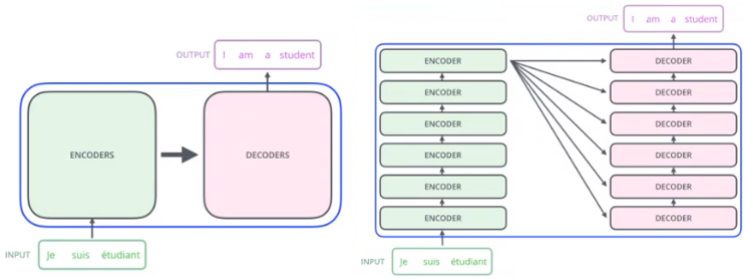
$$m_i = \text{MLP}(\text{Output}_i) + b_2 = W_2 \cdot \text{ReLU}(W_1 \cdot \text{Output}_i + b_1) + b_2$$

Future We need to ensure we don't "look at the future" when predicting a sequence, like in machine translation or language modeling. To mask the future, we could change the set of keys and queries to include only past words but it's inefficient. To enable parallelization, we mask out attention to future words by setting attention scores to $-\infty$

$$e_{ij} = \begin{cases} q^T k_j & j < i \\ -\infty & j \geq i \end{cases}$$

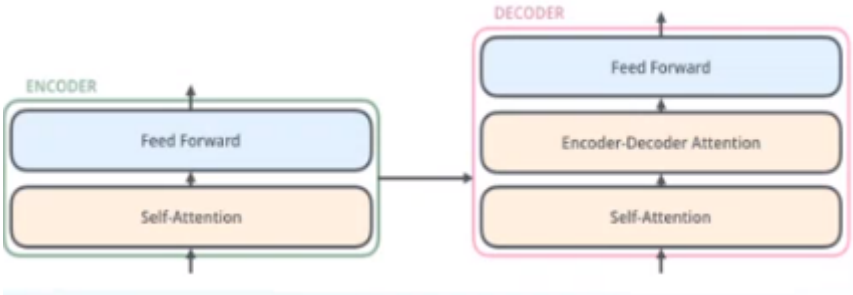
0.13.2 Transformers

The encoder maps an input sequence of symbol representations $(x_1, \dots, x_n)$ to a sequence of continuous representations $(z_1, \dots, z_n)$ Given z, the decoder then generates an output sequence $(y_1, \dots, y_m)$ of symbols one element at a time. At each step, the model is **auto-regressive**, consuming the previously generated symbols as additional input when generating the next.



The encoding component is a stack of encoders, and the decoding component is a stack of decoders of the same number.

Self-Attention The encoder's inputs first flow into a self-attention layer, that helps the encoder look at other words in the input sentence as it encodes a specific word. The outputs of the self-attention layer are fed to a feed-forward neural network: the exact same FFNN in independently applied to each position.
The decoder has both those layers, with an attention layer between them that helps the decoder focus on the relevant parts of the input sentence.



Multi-Headed Attention With a simple self-attention there's only a way for a word to interact with others. We can expand the model ability to focus on different positions: multiple sets of query/key/value weight matrices, apply attention and then concatenate outputs and pipe through linear layer.

1. From the input sentence
2. We embed each word (**word embeddings**)
   In all encoders other than the first we don't need the embedding, we directly use the output of the previous encoder.
3. We split into n heads and multiply with weight matrices
4. Calculate attention using the resulting $Q/K/V$ matrices
5. Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output layer.

Training Tricks

Residual Connections: deep networks are bad at learning the identity function. Therefore, directly passing "raw" embeddings to the next layer can be helpful

$$x_l = F(x_{l-1} + x_{l-1}$$

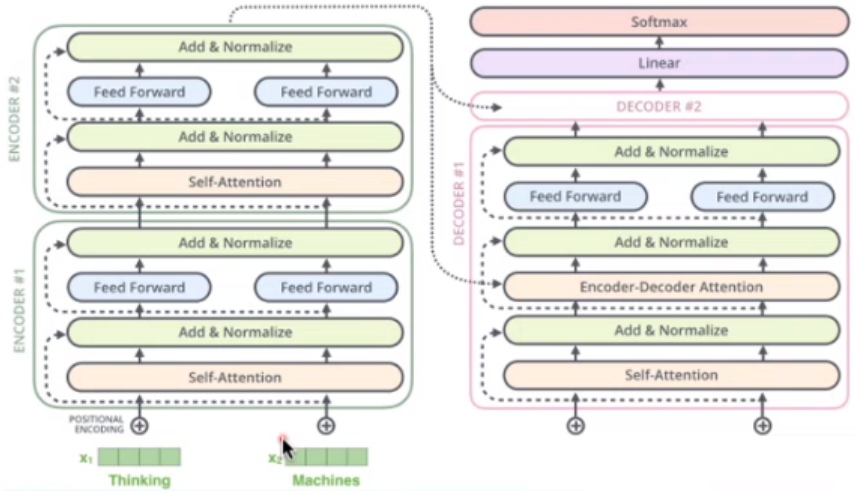
Layer Normalization: may be difficult to train the parameters of a given layer because its input from the layer beneath keeps shifting. Solution: reduce uninformative variation by normalizing to zero mean and std. dev. one within each layer

$$x'_l = \frac{x_l - \mu_l}{\sigma_l + \epsilon}$$

Helps models to train faster.

Scaled Dot Product Attention: after layer normalization, the mean and variance of vector elements is 0 and 1, respectively. However the dot product still tends to take on extreme values, as its variance scales with dimensionality d_k. The updated self-attention equation is

$$\text{Output} = \text{Softmax}\left(\frac{QK^t}{\sqrt{d_k}}\right)V$$



Transformers Library

Hugging Face Transformers Installed with `pip install transformers`.
Typical pattern is to load a model, then initialize two objects:

Tokenizer
Can use specific tokenizer for specific model

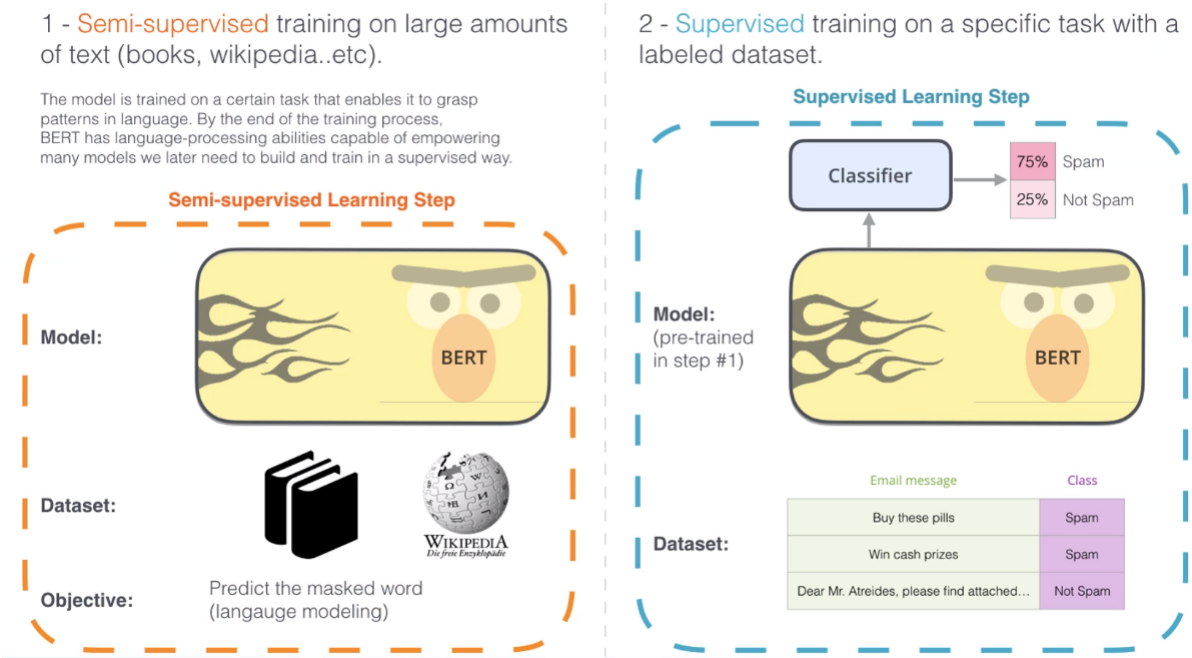
Model, three types: encoders (e.g. BERT), decoders (e.g. GPT2), encoder-decoders

Transformers Architectures

From **pretrained word embeddings**: start with pretrained word embeddings with no context, and learn to incorporate context in an LSTM or transformer while training on the task.
Issues: the training data we have for our downstream task (like question answering) must be sufficient to teach all contextual aspects of language. Also most of the parameters in our network are randomly initialized.

In modern NLP we **pretrain the whole model**: all (or almost all) NLP networks' **parameters are initialized via pretraining**. Pretraining methods hide parts of the inputs from the model, and then train the model to reconstruct those parts.
This has been **effective at building strong representations** of language, parameter initialization for strong NLP models and probability distributions over language that we can sample from.

Pretraining Transformers Two-step development



Pretraining through language modeling Recall the language modelling task: model $P_\theta(w_t \mid w_{1:t-1})$, the probability distributions over words given their past contexts (lots of data for this).
Pretraining through language modeling is training a neural network to perform language modeling on a large amount of texts and **saving the parameters for later**.

Pretraining-Finetuning Paradigm

1. Pretrain on language modeling: learn general things
2. Finetune on your task: adapt to the specific task

SGD

Pretraining a language model provides base parameters $\hat{\theta}$

Finetune a model on a task initializing parameters to $\hat{\theta}$

The training may help because the SGD sticks (relatively) close to $\hat{\theta}$ during finetuning. So, maybe the finetuning local minima near $\hat{\theta}$ tend to generalize well, and/or the gradients of finetuning loss near $\hat{\theta}$ propagate nicely.

Pretraining for Three Types of Architectures

Decoders: language models, nice to generate from, can't condition on future words.
Examples: GPT-3, LaMDA

Encoders: bidirectional context so can condition on future (how to pretrain?)
Examples: BERT and its variants

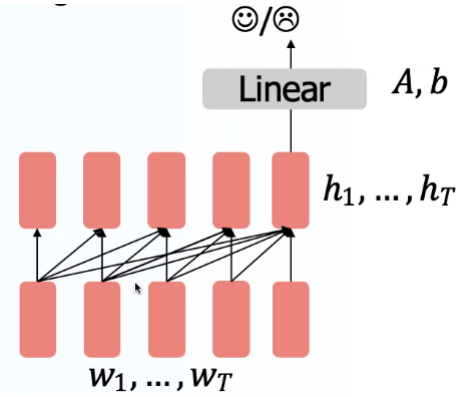
Encoder-Decoders: good parts of both, what's the best way to pretrain them?
Examples: Transformers, Meena

Pretraining Decoders When using language model pretrained decoders, we can ignored that they were trained to model $P_\theta(w_t \mid w_{1:t-1})$. We can finetune them by adding a classifier on the last word hidden state

$$h_1, \ldots, h_T = \text{Decoder}(w_1, \ldots, w_T)$$

$$y \simeq Aw_T + b$$

Where A and b are randomly initialized and specified by the downstream task. Gradients backpropagate through the whole network.



Red means pretrained, so note how **the linear layer hasn't been pretrained and must be learned from scratch**. It's natural to pretrain decoders as language models and then using them as generators, finetuning their $P_\theta(w_t|w_{1:t-1})$. This is helpful in tasks where the output is a sequence, with a vocabulary like that at pretraining time.

$$h_1, \ldots, h_T = \text{Decoder}(w_1, \ldots, w_T)$$

$$w_t \simeq Aw_{t-1} + b$$

With A, b pretrained in the language model.

Generative Pretrained Transformer (GPT): how to format inputs to our decoder for finetuning tasks. E.g. in natural language inference we can label pairs of sentences as entailing/contradictory/neutral.

Pretraining Encoders Encoders get bidirectional context, can't use language modeling. Idea: replace some fraction of words in the input with a "[MASK]" and predict these words

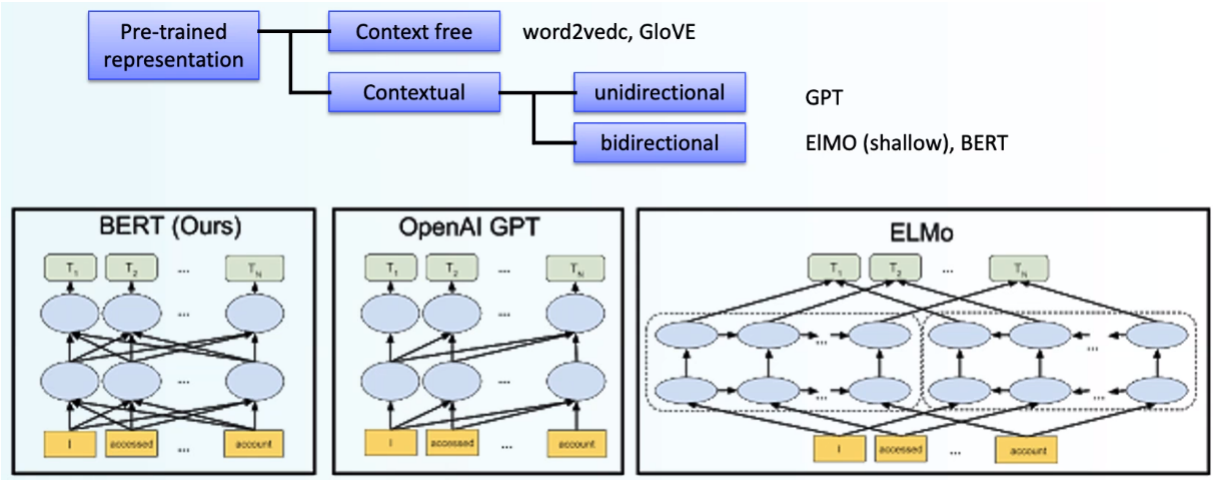
$$h_1, \ldots, h_T = \text{Encoder}(w_1, \ldots, w_T)$$

$$y_i \simeq Aw_i + b$$

Only add loss terms from words that are "masked out". If $\tilde{x}$ is the masked version of x, we're learning $p_\theta(x \mid \tilde{x})$ called **Masked LM**.

Problems with previous methods Language models only use left context **or** right context, but language understanding is bidirectional. Why are language models unidirectional? Directionality is needed to generate a well-formed probability distribution (we don't care about this) and words can "see themselves" in a bidirectional encoder.

BERT This is the first, deeply bidirectional, unsupervised language representation, pre-trained using only a plain-text corpus.
BERT-base is 12 layers, BERT-large is 24 layers, of transformer encoders.



Masked LM Mask out $k\%$ of the words (typically $k = 15$) and predict the masked words. Too little masking: too expensive to train.
Problem: mask token never seen at fine-tuning. Solution: 15% of the words to predict don't replace with [MASK] 100% of the time. Instead: 80% of the time replace with [MASK], 10% replace with random word, and 10% keep the same.
To learn relationships between sentences (**next sentence prediction**), predict whether Sentence B is actual sentence that follows Sentence A, or a random sentence.

Wordpiece These models give a good balance between the flexibility of single characters and the efficiency of full words for decoding. Also sidesteps the need for special treatment of unknown words: common words are in the vocabulary, while other words are built from pieces (e.g. hypathia = h ##yp ##ati ##a)
Wordpiece model: given a training corpus and a number of desired tokes D, select D wordpieces such that the resulting corpus is minimal in the number of wordpieces when segmented according to the chosen wordpiece model.

Pretraining Encoder-Decoders For those we could do something like language modeling, but where a prefix $w_1, \dots, w_T$ of every input is provided to the encoder and is not predicted.

$$h_1, \dots, h_T = \text{Encoder}(w_1, \dots, w_T)$$

$$h_{T+1}, \dots, h_2 = \text{Decoder}(w_1, \dots, w_T, h_1, \dots, h_T)$$

$$y_i \simeq Aw_i + b \quad i > T$$

The encoder portion benefits from bidirectional context, the decoder portion is used to train the whole model through language modeling

What pretraining objective to use? Span corruption.
Replace different-length spans from the input with unique placeholders, then decode out the spans that where removed. This is implemented in text preprocessing. This model, T5, can be finetuned to answer a wide range of questions, retrieving knowledge from its parameters.

Pre-training Tasks

Masked LM

Train a deep bidirectional representation, masking some percentage of the input tokens at random, and then predicting those masked tokens.

The final hidden vectors corresponding to the mask tokens are fed into an output softmax over the vocabulary, as in a standard LM

Next Sentence Prediction

In order to train a model that understands sentence relationships, we pre-train for a binarized next sentence prediction task generated from any corpus.

50% of the time B is an actual sentence that follows A and 50% of the time it's a random sentence.

In-Context Learning So far, pretrained models have been used mainly by **sampling** them (with a prompt) or **finetuning** them on the task we want. Very large language models seem to performe some kind of **learning without gradient steps**, just using the examples that are provided as context. These examples seem to specify the task to be performed.

Distillation Most pretrained language models are extremely large and expensive. The idea of distillation is very simple: train a **teacher** with pretraining and finetuning techniques to achieve maximum accuracy, then label a large amount of examples with the teacher. The **student** will be a much smaller model (e.g. 50x smaller) which is trained to mimic the teacher output with MSE or cross entropy.
An hypothesis on why this works well is that large language models tend to be oversized, because modeling language is the "ultimate" NLP task. In most application tasks only a subset of the features are effectively used, and the student focuses on those features.

0.14 Analysis of Language Models

Aka BERTology

Questions About Language Models

What can be learned via language model pretraining?

What **can't** be learned via language pretraining?

What will replace the Transformer?

What does deep learning try to do?

What do neural models tell us about language?

How these models affect people and transfer power?

What Linguistic Knowledge is Present in LM? POS tagging through word embedding clusters.
NER via Masked Language Model.

Unsupervised NER Given a Masked Language Model, submit a masked sentence, look at possible outputs

LM Effectivness LMs exhibit surprising abilities in several language tasks. But do they really understand language? Consider the Natural Language Inference (NLI) task. What if the model is using simple heuristics to get good accuracy? A diagnostic test set is carefully constructed to test for a specific skill or capacity of your neural model. E.g. HANS (Heuristic Analysis for NLI Systems) tests syntactic heuristics in NLI.

Heuristic	Definition	Example
Lexical overlap	Assume that a premise entails all hypotheses constructed from words in the premise	**The doctor** was **paid** by **the actor**. $\xrightarrow[\text{WRONG}]{}$ The doctor paid the actor.
Subsequence	Assume that a premise entails all of its contiguous subsequences.	The doctor near **the actor danced**. $\xrightarrow[\text{WRONG}]{}$ The actor danced.
Constituent	Assume that a premise entails all complete subtrees in its parse tree.	If **the artist slept**, the actor ran. $\xrightarrow[\text{WRONG}]{}$ The artist slept.

LM as Linguistic Test Subjects How do we understand language behavior in humans? One method: **minimal pairs**, what sounds "okay" to a speaker but doesn't with a small change?
E.g. "*the chef who made the pizzas is here*" vs "*the chef who made the pizzas **are** here*". Idea: verbs agree in number with their subjects, subject-verb relationship.
Assign higher probability to the acceptable sentence in the minimal pair. Just like HANS, we can develop a test set with carefully chosen properties: specifically, can language models handle "**attractors**" in subject-verb agreement?

0 attractors: *the chef is here*

1 attractor: *the chef who made the **pizzas** is here*

2 attractors: *the chef who made the **pizzas** and prepped the **ingredients** is here*

...

Some examples for subject-verb agreement with attractors that a model got wrong:

√ The **ship** that the player drives **has** a very high speed
The **ship** that the player drives ***have*** a very high speed

√ The **lead** is also rather long; 5 paragraphs **is** pretty lengthy...
The **lead** is also rather long; 5 paragraphs ***are*** pretty lengthy...

Prediction Explanations What in the input led to this output? For a single example, what parts of the input led to the observed prediction? **Saliency maps**: a score for each input word indicating its importance to the model's prediction.
To make a saliency map, there are many ways to encode the intuition of "importance".

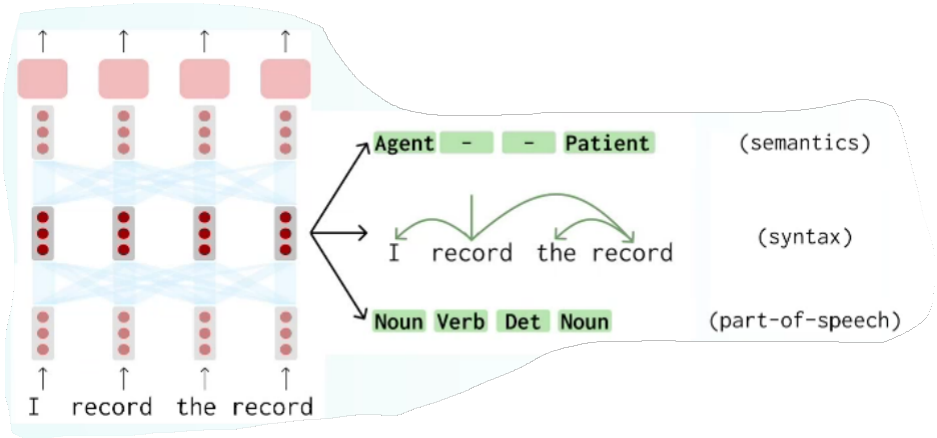
> **Simple gradient method**: for words $x_1, \ldots, x_n$ and the model's score for a given class (output label) $s_c(x_1, \ldots, x_n)$ take the norm of the gradient of the score with respect to each word
>
> $$\text{Salience}(x_i) = \|\nabla_{x_i} s_c(x_1, \ldots, x_n)\|$$
>
> High gradient norm means changing the word locally would affect the score a lot, so it's very important. Not perfect: linear approximation may not hold well. There are many more methods proposed.

Another way is explanation by input reduction, making changes to the document and judge how much it would affect the result. What is the smallest part of the input I could keep and still get the same answer? Idea: run an input saliency method, iteratively removing the less important words.
Another way is analyzing models by breaking them: can we break models by making seemingly innocuous changes to the input?

0.14.1 Probes

Probing Supervised analysis of neural networks.

Premise: pretrained transformers provide surprisingly good general-purpose language representations?
Question: what do pretrained representations encode about lingustic properties which we have annotated data?



We have some property y (like POS). We have the model's word representations at fixed layer $h_1, \ldots, h_T$ where $h_i \in R^d$ where the words are at indices $1, \ldots, T$. We also have a function family F like the set of linear models, or 1-layer FFNN with fixed hyperparameters. We **freeze** the parameters of the model, so its not finetuned, then we train our probe: a function

$$\hat{y} \simeq f(h_i)$$

with $f \in F$.
The extent to which we can predict y from h_i is a measure of the accessibility of that feature in the representation. This helps in gaining a rough understanding into how the model processes its inputs. Also may help in the search for causal mechanisms.

Contextual Representation of Language These pretrained embeddings specify a function which maps elements v in a (word) vocabulary V to vectors $h \in R^d$

$$f_{vocab} : V \to R^d$$

$$v \mapsto h$$

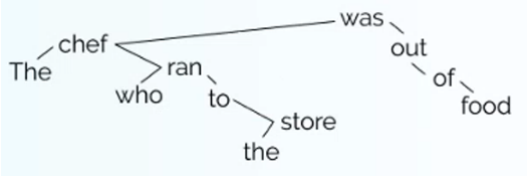
Subword methods consider also literal character sequence, mapping from tuples of vocabulary item v and character sequence $(c_1, \ldots, c_t)$ to vectors

$$f_{subword} : (v, (c_1, \ldots, c_t)) \mapsto h$$

Contextual representations of language leverage the intuition that the meaning of a particular word in a particular text depends on the words that surround it at that moment. Let $w_1, \ldots, w_N$ be a sentence, where $w_i \in V$ is a word. A contextual representation of language is

$$f_{contextual} : (w_1, \ldots, w_N) \mapsto (h_1, \ldots, h_N)$$

Structural Probe In order to perform LM well, with enough data, one implicitly has to know seemingly high-level language information. We think of there existing a latent parse tree on every sentence, which the neural network does not have access to. For the dependency parsing formalism, each word in the sentence has a corresponding node in the parse tree. An example of dependency parse tree:



Our first intuition is that vector spaces and graphs both have natural distance metrics. For a parse tree, we have the **path metric** $d(w_i, w_j)$, which is the number of edges in the path between words w_i and w_j in the tree.

Syntax Distance Hypothesis There exists a linear transformation B of the word representation space under which vector distance encodes parse trees.
Equivalently, there exists an inner product on the word representation space such that distance under the inner product encodes parse trees. This (indefinite) inner product is specified by $B^T B$.

Finding a Parse Tree Encoding Distance Metric Our potentially tree-encoding distances are parametrized by the linear transformations $B \in R^{k \times n}$

$$\|h_i - h_j\|_B^2 = B(h_i - h_j)^T B(h_i - h_j)$$

Bh is the linear transformation of the word representation, or equivalently it is the parse tree node representation. This is equivalend to finding an L2 distance on the original vector space, parametrized by the positive semi-definite matrix $A = B^T B$

$$\|h_u - h_j\|_A^2 = (h_i - h_j)^T A(h_i - h_j)$$

Finding B B is chosen to minimize the difference between true parse tree distances from a human-parsed corpus and the predicted distances from the fixed word representations transformed by B

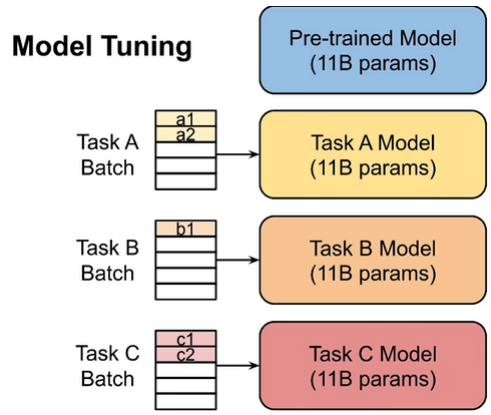
$$\min_B \sum_l \frac{1}{|s_l|^2} \sum \left(d(w_i, w_j) - \|B(h_i, h_j)\|^2 \right)$$

Conclusion The geometry of english parse trees is approximately discoverable in the geometry of deep models of a language. Dependency syntax is not the only graph structure on might try to find in a linear transformation of a hidden state space, other graph structures might be found as well.

0.15 Prompt-Based Learning

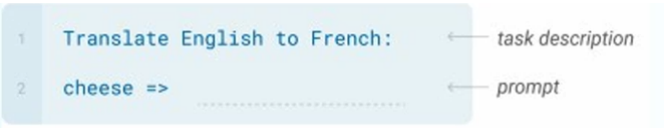
Given the increasing complexity of the models, in terms of number of parameters which currently are in the orders of several hundreds of billions, more and more solutions require reusing existing models.

Finetuning Given a pretrained model and a labeled dataset, update weights of pretrained model by supervised learning on a labeled dataset. Strong performance on many tasks, and the starting point of most state of the art methods today, with smaller dataset for finetuning.
Each trained model is a fork. These models are so big even finetuning often takes complex SPMD programming and a large computing platform.
Serving can be difficult: a different model for each task, need enough requests to keep model saturated, swapping models into memory can take a long time. There's also a **practical challenge**: large models are costly to share and use.



The traditional finetuning technique is to train the model via repeated gradient updates using a large corpus of example tasks. Give an example, perform gradient update, next example and next gradient update... and so on.

Zero-shot The model predicts the answer given only a natural language description of the task. No gradient updates are performed.



Not fine-tuning! Literally just take a pretrained Language Model and give it the prefix "Translate English to French: cheese →"

One-Shot In addition to the task description, the model sees a single example of the task. No gradient updates.

Just give it the prefix "Translate English to French: sea otter → loutre de mere, cheese →"

Few-Shot Similarly give it few examples, 100 max.

0.15.1 Prompts

Sub-optimal and sensitive discrete/hard prompts (natural language instruction/tasks descriptions).
Problems: requiring domain expertise/understanding of the model's inner workings, performance still lags behind state-of-the-art model tuning results, and sub-optimal and sensitive. Prompts that humans consider reasonable are not necessarily effective for language models, and pre-trained language models are sensitive to the choice of the prompts.

Prompt	P@1
[X] is located in [Y]. *(original)*	31.29
[X] is located in which country or state? [Y].	19.78
[X] is located in which country? [Y].	31.40
[X] is located in which country? In [Y].	51.08

Table 1. Case study on LAMA-TREx P17 with bert-base-cased. A single-word change in prompts could yield a drastic difference.

Shifting from discrete/hard to continuous/soft prompts: additional learnable parameters injected into the model. **Prompt-based learning**:

Manual prompt design

Mining and paraphrasing based methods to automatically augment the prompt sets

Gradient-based search for improved discrete/hard prompts

Automatic prompt generation using a separate generative language model

Learning continuous/soft prompts

Remains unclear how to learn continuous/soft prompts effectively:

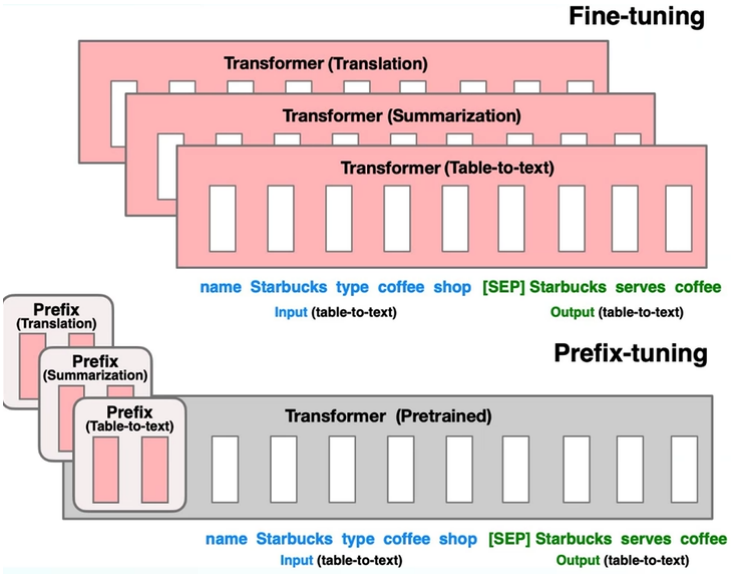
Encode dependencies between prompt tokens using a BiLSTM network

Inject prompts at different positions of the input/model

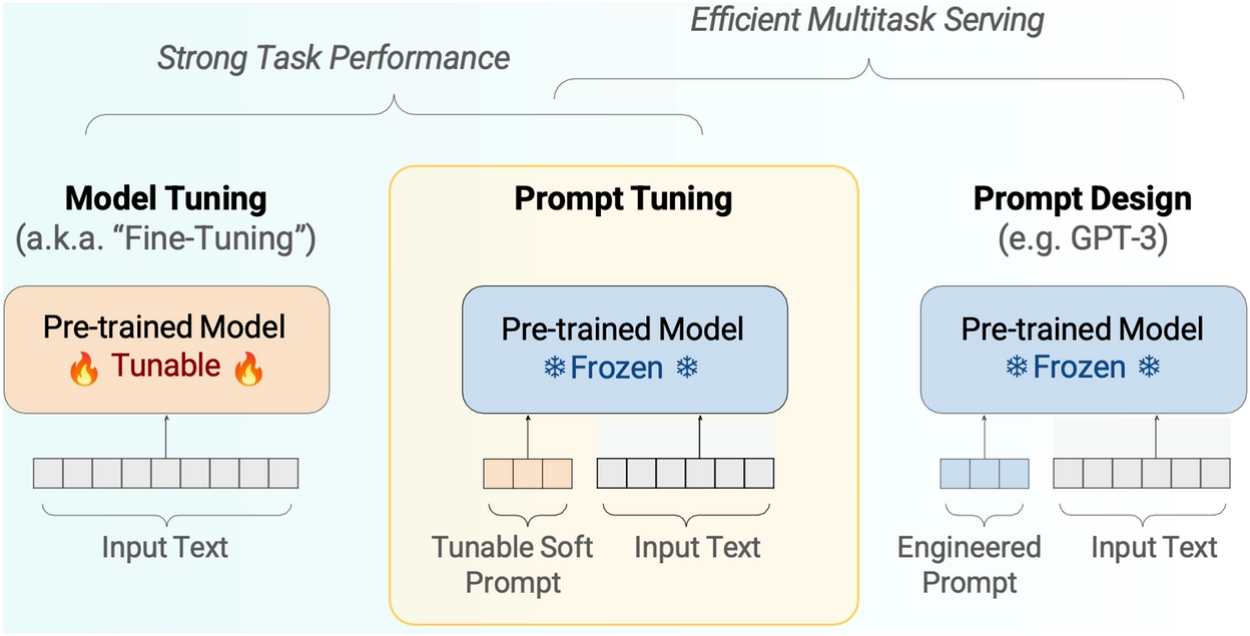
Use mixed prompt initialization strategies

Use ensemble method (e.g. mixture-of-experts)

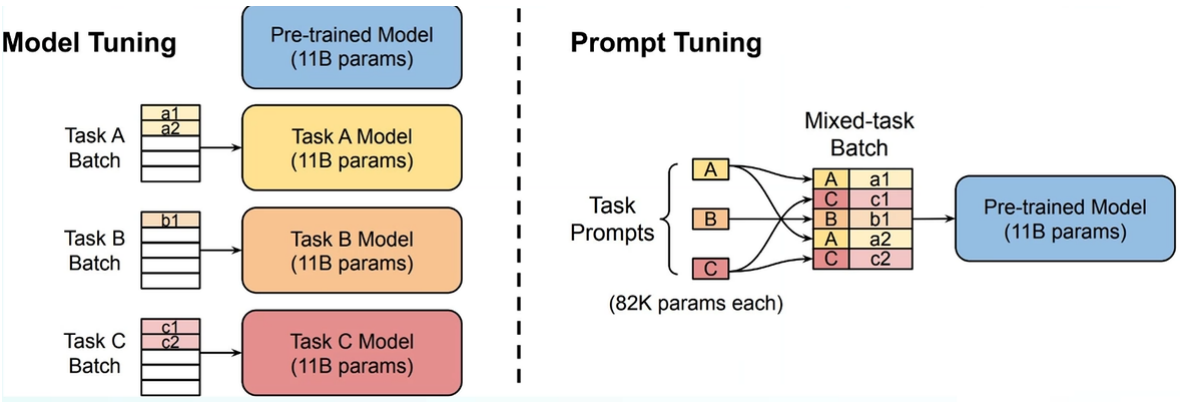
Prefix Tuning Freezes the Language Model parameters and only optimizes the prefix. Adds additional parameters to represent the prefix.



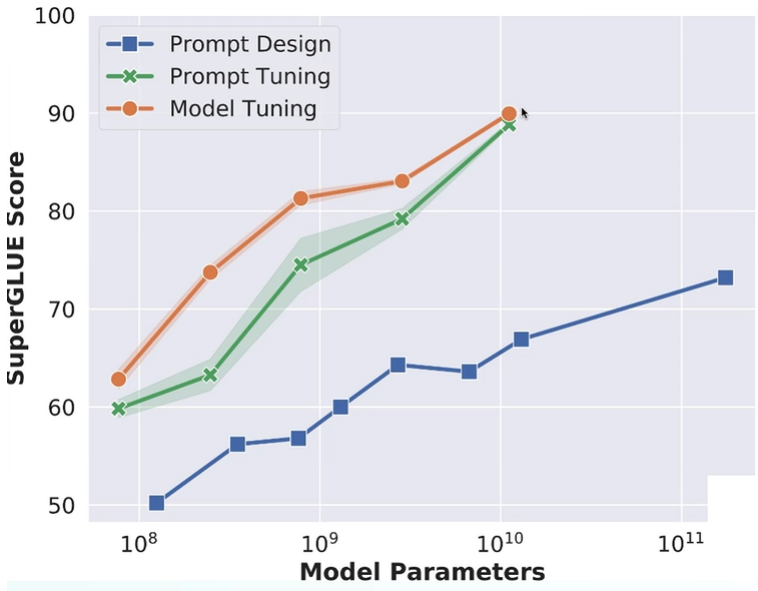
Prompt Tuning Instead of tuning the model we tune the prompt fed to it.



A prompt in prompt tuning is a sequence of additional task-specific tunable tokens prepended to the input text.



This approach becomes more competitive with scale:

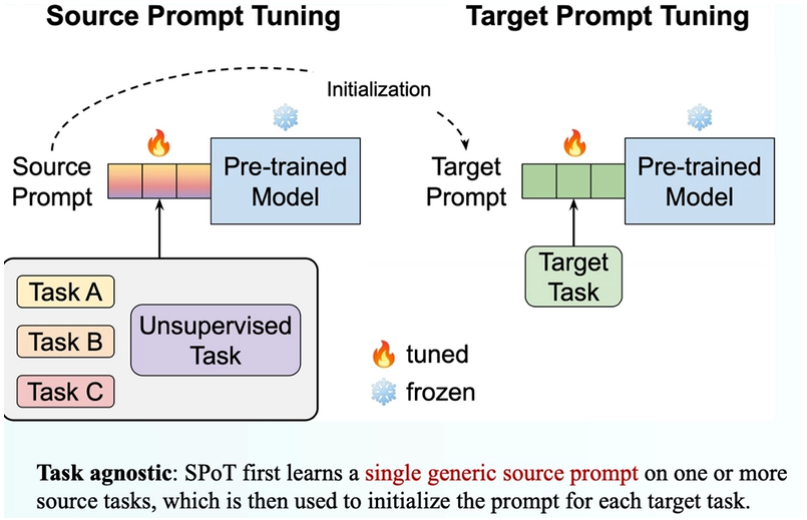


But prompt length matters less with larger pretrained Language Models.

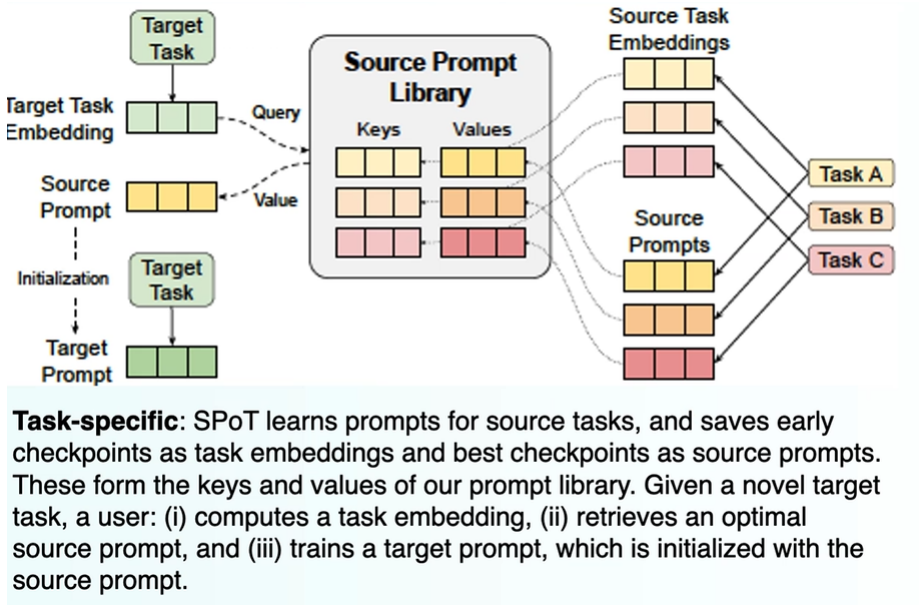
Prompt-Tuning Ensembles Efficient ensembling of models: instead of training N models, we train N prompts (far smaller). Instead of N forward passes through N models, prompt tuning lets use replicate the input, prepending different prompts, and perform a single forward pass with a batch size of N.

Interpretability Soft prompts are learned in embedding spaces, with no need to convert back to tokens. Strong semantic clusters in the top-5 neighbors to each token in the prompt by cosine distance.
We see class labels of neighbors in prompts. They persist in the "class-label" setting and are learned in the other initialization methods.

0.15.2 Soft Prompt Transfer



Task specific



Task embeddings capture task relationships: similar tasks are grouped together into clusters.

0.16 Reading Comprehension

Taxonomy of Question Answering

Information source: a text passage, all web documents, knowledge bases, tables, images...

Question types: factoid vs non-factoid, open-domain vs close-domain, simple vs compositional...

Answer type: a short segment of text, a paragraph, a list, yes or no...

Mort state-of-the-art question answering systems are built on top of end-to-end training and pre-trained language models (e.g. BERT)

Difference Between QA Tasks

Open Domain Question Answering
Relies on external memory consisting of large corpora of documents that may be preprocessed to build information retrieval systems (inverted index, ranking...)

Answer Selection
Focuses on choosing on the fly most likely passage containing the right answer from a small given list

Reading Comprehension
Find the answer withing a given paragraph (no preprocessing, no memory)

Dialogue Systems
Must provide answers to questions and also keep memory of dialog context, remembering previous statements. May rely on Open Domain Question Answering for answering general questions

Inferential Question Answering
Provide an answer that requires inference from knowledge resources

Machine Comprehension "A machine comprehends a passage of text if, for any question regarding that text that can be answered correctly by a majority of native speakers, that machine can **provide a string which** those speakers would agree both **answers that question** and **does not contain information irrelevant** to the question."
It's a useful technique for many practical applications, and an important testbed for evaluating how well computer systems understand human language. Also, many NLP tasks can be reduced to reading comprehension.
"Since questions can be devised to query any aspect of text comprehension, the ability to answer questions is the strongest possible demonstration of understanding."

SQuAD Stanford Question Answering Dataset: 100k annotated (passage, question, answer) triples. Passages are selected from English Wikipedia, 100-150 words, and questions are crowd-sourced. Each answer is a short segment of text in the passage: this is a **limitation**, not all questions can be answered this way.
Large scale supervised datasets are also a key ingredient for training effective neural models for reading comprehension. SQuAD is a popular reading comprehension dataset. It's "almost solved" today, and the state-of-the-art exceeds the estimated human performance.

Evaluation Authors collected 3 gold answers. Systems are scored on two metrics:

Exact Match: 1/0 accuracy on whether you match one of the 3 answers

F1: take system and each gold answer as a bag of words and evaluate

Precision: $P = \frac{TP}{TP+FP}$

Recall: $R = \frac{TP}{TP+FN}$

F1: $\frac{2 \cdot P \cdot R}{P+R}$

The score is a (macro-)average of per-question F1 scores. The F1 measure is seen as more reliable and taken as primary: it's less based on choosing exactly the same span that humans choose, which is susceptible to various effects including line breaks.
Both metrics ignore punctuation and articles.
Estimated human performance is $EM = 82.3$, while the $F1 = 91.2$

SQuAD 2.0 A defect of SQuAD is that all questions have answers in the paragraph. System implicitly rank candidates and choose the best one, you don't have to judge whether a span answers or not the question.
In SQuAD 2.0, 33% of the training questions have no answer and about 50% of the dev/test questions have no answer. For NoAnswer examples, NoAnswer receives a score of 1 and any other response gets 0, both for exact match and F1. The simplest system to approach this is to have a threshold score for whether a span answers a question, or you could have a second component that confirms answering, like Natural Language Inference or "Answer Validation".

0.16.1 Neural Models for Reading Comprehension

How can we build a model to solve SQuAD? Problem formulation:

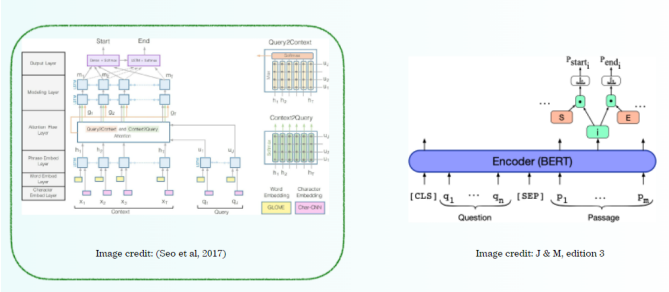
Input, $c_i, q_i \in V$

$C = (c_1, \ldots, c_N), N \simeq 100$

$Q = (q_1, \ldots, q_M), M \simeq 15$

Output: $1 \leq \text{start} \leq \text{end} \leq N$

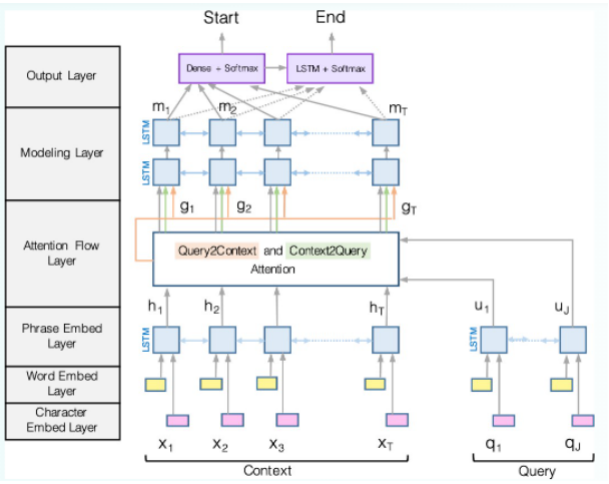
LSTM-based vs BERT-based



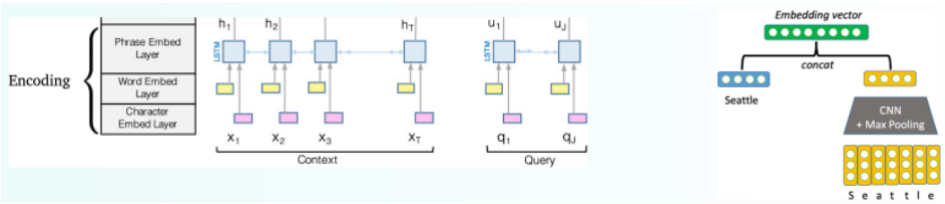
Seq2Seq w/ Attention (recap) Instead of a source and a target sentences, we have two sequences: passage and question, with unbalanced lengths. We need to model which words in the passage are most relevant to the question and which question words. Attention is the key ingredient, similar to which words in the source sentence are most relevant to the current target word. We don't need an autoregressive decoder to generate the target sentence word-by-word. Instead, we just need to train two classifiers to predict the start and end positions of the answers.

BiDAF

Bidirectional Attention Flow Model



Encoding



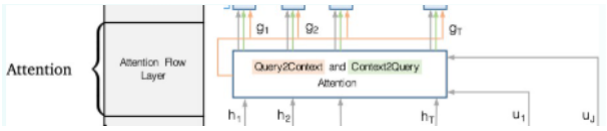
Use a concatenation of word embedding (GloVe) and character embedding (CNNs over character embeddings) for each word in context and query.

$$e(c_i) = f([\text{GloVe}(c_i); \text{charEmb}(c_i)]) \qquad e(q_i) = f([\text{GloVe}(q_i); \text{charEmb}(q_i)])$$

Then use two **bidirectional** LSTMs separately to produce contextual embeddings for both context and query.

$$\overrightarrow{c}_i = \text{LSTM}(\overrightarrow{c}_{i-1}, e(c_i)) \in R^H \qquad \overrightarrow{q}_i = \text{LSTM}(\overrightarrow{q}_{i-1}, e(q_i)) \in R^H$$
$$\overleftarrow{c}_i = \text{LSTM}(\overleftarrow{c}_{i-1}, e(c_i)) \in R^H \qquad \overleftarrow{q}_i = \text{LSTM}(\overleftarrow{q}_{i-1}, e(q_i)) \in R^H$$
$$c_i = [\overrightarrow{c_i}; \overleftarrow{c_i}] \in R^{2H} \qquad q_i = [\overrightarrow{q_i}; \overleftarrow{q_i}] \in R^{2H}$$

Attention



Context-to-query attention: for each context word, choose the most relevant words from the query words.

First, compute a similarity score for every pair (c_i, q_i) with $w_{sim} \in R^{6H}$

$$S_{ij} = w_{sim}^T [c_i; q_i; c_i \odot q_i] \in R$$

Context-to-query attention (which question words are more relevant to c_i)

$$\alpha_{ij} = \text{Softmax}_i(S_{ij}) \in R$$
$$a_i = \sum_{j=1}^{M} \alpha_{ij} q_j \in R^{2H}$$

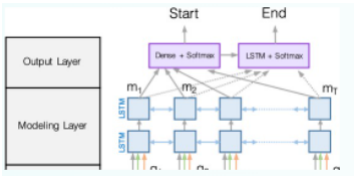
Query-to-context attention (which context words are relevant to some question words):

$$\beta_i = \text{Softmax}_i \left(\max_{j=1}^{M} (S_{ij}) \right) \in R^N$$
$$b = \sum_{i=1}^{N} \beta_i c_j \in R^{2H}$$

The final output is

$$g_i = [c_i; q_i; c_i \odot a_i; c_i \odot b] \in R^{8H}$$

Modeling and Output Layers



Modeling Layer pass g_i to another two layers of bidirectional LSTMs.
Attention layer is modeling interaction between query and context, while modeling layer is modeling interaction within context words

$$m_i = \text{BiLSTM}(g_i) \in R^{2H}$$

Output Layer two classifiers predicting the start and end positions

$$p_{start} = \text{Softmax}_i(w_{start}^T [g_i; m_i])$$
$$p_{end} = \text{Softmax}_i(w_{end}^T [g_i; m_i'])$$
$$m_i' = \text{BiLSTM}(m_i) \in R^{2H}$$
$$w_{start}, w_{end} \in R^{10H}$$

The final training loss is

$$L = -\log p_{start}(s^*) - \log p_{end}(e^*)$$

BERT

BERT is a deep bidirectional Transformer encoder pre-trained on large amounts of text with two training objectives:

MLM (Masked Language Model)

NSP (Next Sentence Prediction)

BERT for Reading Comprehension The question is the first text segment, Segment A, and the passage is Segment B. The answer is predicting two endponts in Segment B.

$$L = -\log p_{start}(s^*) - \log p_{end}(e^*)$$

$$p_{start} = \text{Softmax}_i(w_{start}^T H)$$

$$p_{end} = \text{Softmax}_i(w_{end}^T H)$$

with $H = [h_1, \ldots, h_N]$ the hidden vectors of the paragraph returned by BERT.
All the BERT parameters, 100M, as well as the newly introduced parameters h_{start}, h_{end} (768·2=1536) are optimized together for L. It works amazingly well, stronger pre-trained language models can lead to even better performance and SQuAD become a standard dataset for testing pre-trained models.

Comparing BiDAF and BERT

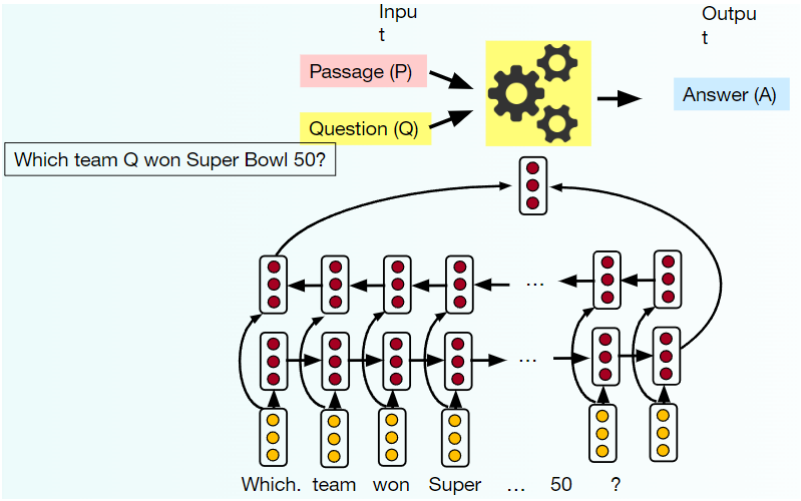
BERT has 110M-330M parameters, while BiDAF has ≃2.5M

BERT is built on top of Transformers, while BiDAF is built on top of several BiLSTMs

BERT is pre-trained while BiDAF is only built on top of GloVe

Stanford Attentive Reader

Demonstrated a minimal, highly successful architecture for reading comprehension and question answering.



SpanBERT

Better pre-training. Two ideas:

Masking contiguous spans of words instead of 15% random words.

Using the two end points of span to predict all the masked words in between = compressing the information of a span into its two endpoints.

$$y_i = f(x_{s-1}, x_{e+1}, p_{i-s+1})$$

0.16.2 State-of-the-Art

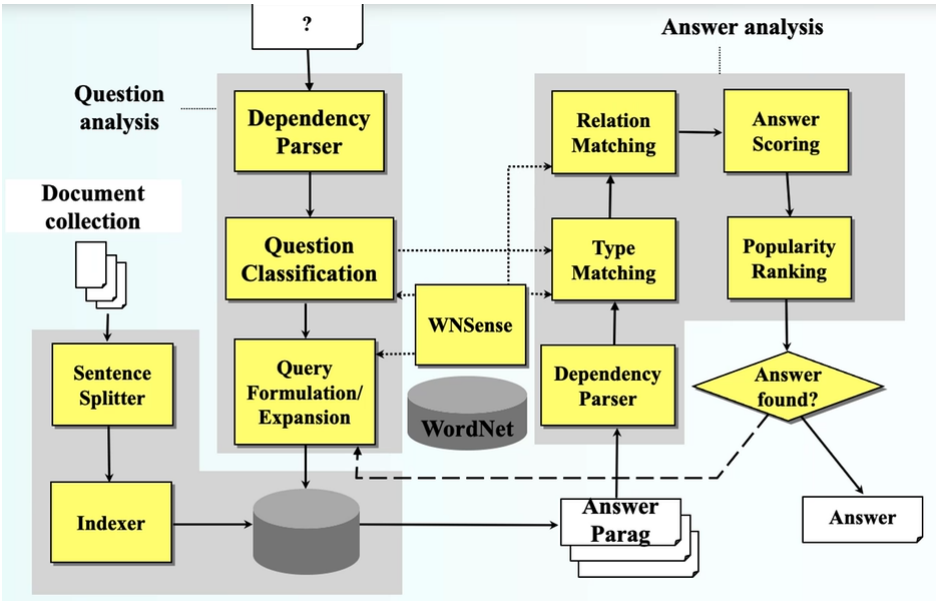
Is Reading Comprehension Solved? We have already surpassed human performance on SQuAD, but of course reading comprehension isn't solved. The current systems still perform poorly on adversarial examples or examples from out-of-domain distributions. Also, systems trained on one dataset can't generalize to other datasets.

0.17 Open Domain Question Answering

We've seen how transformer models are suitable for reading comprehension, with or without finetuning.

Different from reading comprehension because we don't assume a given passage, no "source" for the answer. Instead, we have access to a large collection of documents (e.g. Wikipedia). We don't know where the answer is located, and the goal is to return the answer for any open-domain question. Much more challenging, then.

PiQASso Pisa Question Answering System



Question Analysis Given the question:

1. **Parsing**: natural language question is parsed
2. **Keywords extraction**: POS tags are used to select search keywords
3. **Answer type detection**: expected answer type is determined applying heuristic rules to the dependency tree
4. **Relation detection**: additional relations are inferred and the answer entity is identified

Memory Vanilla NN only store memory in their parameters, which can be billions from billions of documents, but cannot be extended through usage.
Open Domain Question Answering must combine

Access to external memory (**Document Retriever**)

Reading comprehension (**Document Reader**)

Retriever-Reader Framework Input: a large collection of documents $D = \{D_1, \ldots, D_n\}$ and a question Q.
Output: an answer string A

Retriever $f(D, Q) = P_1, \ldots, P_k$ (with k predefined and small, e.g. 100)

Reader $g(Q, \{P_1, \ldots, P_k\}) = A$, reading comprehension problem

The retriever is a standard TF-IDF information retrieval sparse model (a fixed module). The reader is a neural reading comprehension model trained on SQuAD an other distantly-supervised QA dataset.
Distantly supervised examples $(Q, A) \to (P, Q, A)$.

Document Reader Each token p_i in a paragraph $\{p_1, \ldots, p_m\} = RNN(\{\tilde{p}_1, \ldots, \tilde{p}_m\})$.
Each feature vector $\tilde{p}_i$ is comprised of the following parts:

Word embeddings $f_{emb}(p_i) = E(p_i)$

Exact match $f_{exact}(p_i) = I(p_i \in q_i)$, three simple binary features indicating whether p_i can be exactly matched to one question word in q

Token features $f_{token}(p_i) = (POS(p_i), NER(p_i), TF(p_i))$

Aligned question embedding $f_{align}(p_i) = \sum_j a_{ij} E(q_j)$ using attention scores

$$a_{ij} = \frac{e^{\alpha(E(p_i))\alpha(E(q_j))}}{\sum_{j'} e^{\alpha(E(p_i))\alpha(E(q_{j'}))}}$$

with α being a ReLU dense layer.

Question encoding $q = \sum_j b_j q_j$ where b_j encodes the importance of each question word $b_j = \frac{e^{wq_j}}{\sum_{j'} e^{wq_{j'}}}$
For the prediction train two classifier

$P_{start}(i) \propto e^{p_i W_s q}$

$P_{end}(i) \propto e^{p_i W_e q}$

Find $i, i' \mid i \leq i' \leq i + 15 \wedge P_{start}(i) \cdot P_{end}(i')$ is maximized.

We can train the retriever too, even joint training of retriever and reader. Each text passage can be encoded as a vector using BERT and the retriever score can be measured as the dot product between the question representation and passage representation. However it's not easy to model, huge number of passages (e.g. 21M in English Wikipedia).
We can also just train the retriever using question-answer pairs (DPR, Dense Passage Retrieval).
Recent works shows that it is beneficial to generate answers instead of extracting answers.
Large language models can do open-domain question answering as well, without an explicit retriever stage. The reader model may be unnecessary as well. It's possible to encode all the phrases using dense vectors and only do nearest neighbor search without a BERT model at inference time.

Inference Question Answering	**Reading Comprehension**
Story T	Document D
Question q	Question q
Answer q performing inference over T	Find span in D representing the answer

Facebook's bAbI Dataset Collection of 20 tasks, each check one skill that a reasoning skill should have. Aims at systems able to solve all tasks: no task specific engineering.

Task 1: single supporting fact.
Questions where a single supporting fact, previously give, provides the answer. Simplest case: asking for the location of a person.

Task 2: two supporting facts.
Questions where two supporting statements have to be chained to answer the question.

Task 3: three supporting facts.

Task 4: two argument relations.
To answer questions the ability to differentiate and recognize subjects and objects is crucial. We consider the extreme case: sentences featuring re-ordered words.

Task 6: Yes/No questions

Task 7: Counting

Task 17: positional reasoning (task 6 is a prerequisite)

Task 18: reasoning about size (task 3 and 6 are prerequisites)

Task 19: pathfinding.
Goal is finding the path between locations. Difficult, it effectively involves search.

Task 20: agent's motivation

Type	Task number	Difficulty
Single Supporting Fact	1	Easy
Two or Three Supporting Facts	2-3	Hard
Two or Three Argument Relations	4-5	Medium
Yes/No Questions	6	Easy
Counting and Lists/Sets	7-8	Medium
Simple Negation and Indefinite Knowledge	9-10	Hard
Basic Coreference, Conjunctions and Compound Coreference	11-12-13	Medium
Time Reasoning	14	Medium
Basic Deduction and Induction	15-16	Medium
Positional and Size Reasoning	17-18	Hard
Path Finding	10	Hard
Agent's Motivations	20	Easy

Question Dependent Recurrent Entity Network for Question Answering Based on the Memory Network Framework as a variant of Recurrent Entity Network.

Input encoder: creates an internal representation.

Dynamic memory: stores relevant information about entities (Person, Location,...)

Output module: generates the output.

The idea is to **include the question q in the memorization process**.

Input encoder Set of sentences $\{s_1, \dots, s_t\}$ and a question q

$E \in R^{|V| \times d}$ embedding matrix, $E(w) = e \in R^d$

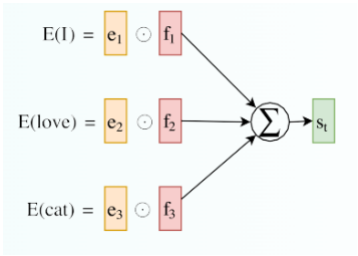
$\{e_1^{(s_t)}, \dots, e_m^{(s_t)}\}$ vectors for the words in s_t

$\{e_1^{(q)}, \dots, e_k^{(q)}\}$ vectors for the words in q

$f^{(s/q)} = \{f_1, \dots, f_m\}$ multiplicative mask with $f_i \in R^d$

$$s_t = \sum_{i=1}^{m} e_i^{(s)} \odot f_i^{(s)}$$

$$q_t = \sum_{i=1}^{k} e_i^{(q)} \odot f_i^{(q)}$$



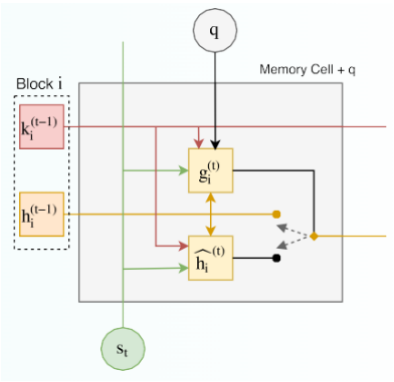
Dynamic Memory Consists in a set of blocks meant to represent entities in the story. A block is made by a key k_i that identifies the entity and a hidden state h_i that store information about it.

$$g_i^{(t)} = \sigma(s_t^T h_i^{(t-1)} + s_t^T k_i^{(t-1)} + s_t^T q)$$

$$\hat{h}_i^{(t)} = \phi(U h_i^{(t-1)} + V k_i^{(t-1)} + W s_t)$$

$$h_i^{(t)} = h_i^{(t-1)} + g_i^{(t)} \odot \hat{h}_i^{(t)}$$

$$h_i^{(t)} = \frac{h_i^{(t)}}{\|h_i^{(t)}\|}$$



Output Module Scores memories h_i using q, with an embedding matrix $E \in R^{|V| \times d}$ to generate the output $\hat{y}$

$$p_i = \text{Softmax}(q^T h_i)$$

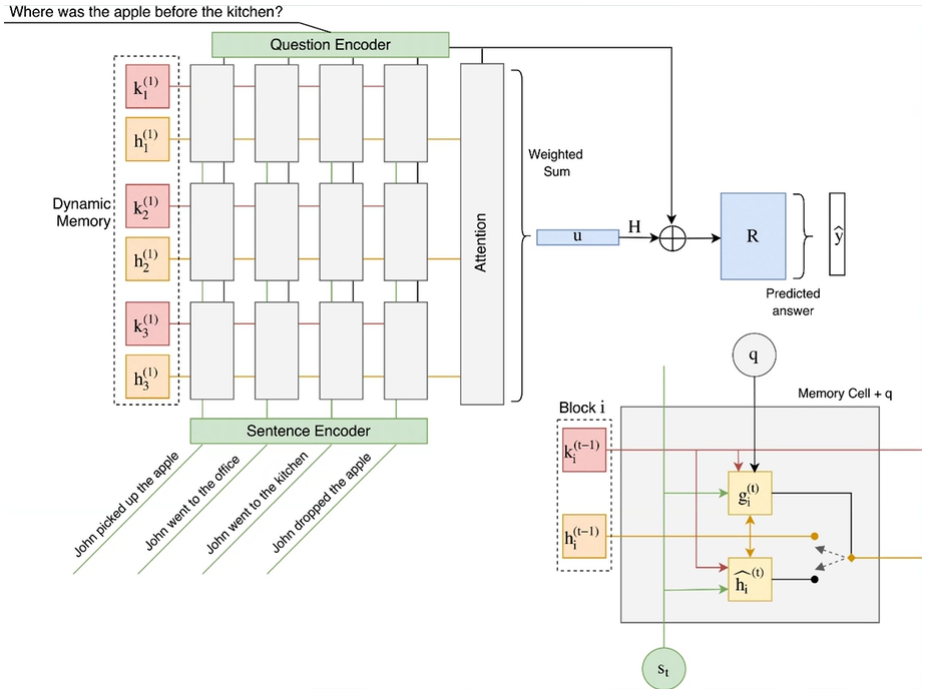
$$u = \sum_{j=1}^{z} p_i h_i$$

$$\hat{y} = R\phi(q + Hu)$$

where $\hat{y} \in R^{|V|}$ represents the model answer.

Training Given $\{(x_i, y_i)\}_{i=1}^n$, use the Cross Entropy loss function $H(y, \hat{y})$ in an end-to-end training with standard backpropagation through time (BPTT) algorithm.

Architecture



0.18 Coreference Resolution

Coreference Resoultion Is identifying all mentions that refer to the same real-world entity.

> **Barack Obama** nominated Hillary Rodham Clinton as **his** secretary of state on Monday. **He** chose her because she had foreign affairs experience as a former First Lady.

Applications

Full text understanding: information extraction, question answering, summarization...

Machine Translation

Dialogue Systems

Coreference Resolution in two steps

1. Detect the mentions, which can be nested, easy
2. Cluster the mentions, hard

Mention Detection Mention: a span of text referring to some entity. Three kinds of mentions:

Pronouns: "I", "your", "him"...

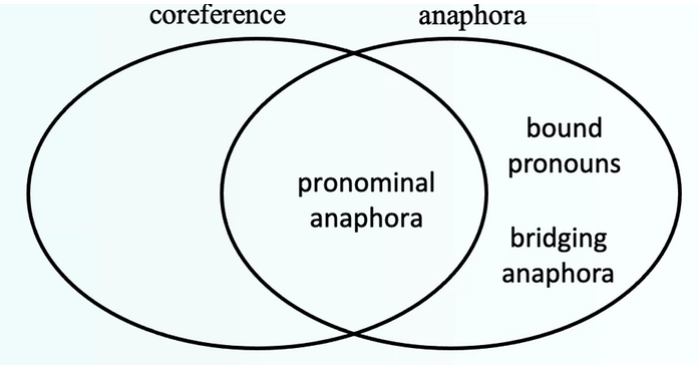
Named Entities: "people", "places"...

Noun Phrases: "a dog", "the big fluffy cat stuck in the tree"...

For detection, use other NLP systems. E.g.: for pronouns use POS tagger, name entities use a NER system (like hw3), for noun phrases use a parser.
Mention detection is not so simple, marking all pronouns, named entities and noun phrases as mentions over-generates mentions. Could train a classifier to filter out spurious mentions, or keep all mentions as "candidate" mentions. After the coreference system is done running, discard all singleton mentions (the one not marked as coreference with anything else).

Can We Avoid a Pipelined System? We could instead train a classifier specifically for mention detection instead of using a POS tagger + NER system + parser. Or even jointly do mention-detection and coreference resolution end-to-end instead of two steps.

Anaphora A related linguistic concept to coreference is **anaphora**: when a term (anaphor) refers to another term (antecedent). The interpretation of the anaphor is in some way determined by the interpretation for the antecedent. Coreference are two words to the same entity, while anaphora are a word ("he") referring another word ("Obama") which refers an entity (the President Barack Obama).
But not all anaphoric relations are coreferential. Not all nouns phrases have reference.
"*We went to see* ***a concert*** *last night.* ***The tickets*** *were really expensive.*" This is referred to as bridging anaphora, no direct link but an implicit one.



Usually, the antecedent comes before the anaphor, but not always.

Context It's often said that language is interpreted "in context". We've seen some examples, like word-sense disambiguation. Coreference is another key example of this. As we progress through an article, dialogue, webpage... we build up a (potentially very complex) **discourse model**, and we interpret new sentences/utterances with respect to our model of what's come before. Coreference and anaphora are all we see in this class of whole-discours meaning, but it's a big part of human language understanding.

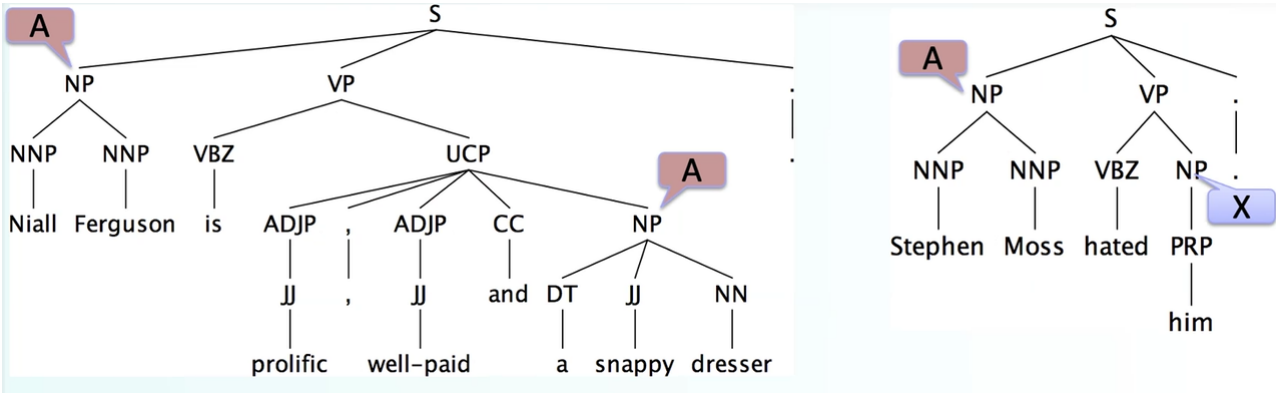
0.18.1 Coreference Models

Three approaches

- Rule-based
- Mention pair/ranking
- Clustering

Rule-Based Approach

Hobb's Naive Algorithm



1. Begin at the NP immediately dominating the pronoun

2. Go up the tree to first NP or S, and call this X and the path p
3. Traverse all branches below X to the left of p, left-to-right breadth-first.
   Propose as antecedent any NP that has a NP or S between it and X
4. If X is the highest S in the sentence, traverse the parse trees of the previous sentences in the order of recency.
   Traverse each tree left-to-right, breadth-first. When an NP is encountered, propose as antecedent.
   If X is not the highest node, go to step 5.
5. From node X go up the tree to the first NP or S. Call it X, and the path p.
6. If X is an NP and the path p to X came from a non-head phrase of X (a specifier or adjunt, such a possessive, PP, apposition, or relative clause), propose X as antecedent
7. Travers all branches below X to the left of the path, in a left-to-right breadth-first manner. Propose any NP encountered as the antecedent
8. If X is an S node, traverse all branches of X to the right of the path, but do not go below any NP or S encountered.
   Propose any NP as the antecedent
9. Go to step 4

"*The naive approach is quite good. Computationally speaking, it will be a long time before a semantically based alghorithm is sophisticated enough to perform as well, and these results set a very high standard for any other approach to aim for.*
Yet, there is every reason to pursue a semantically based approach. The naive algorithm does not work. Any one can think of examples where it fails. In these cases it not only fails, it gives no indication that it has failed and offers no help in finding the real antecedent."

Knowledge-based Pronominal Coreference Two examples:

> She poured water from **the pitcher** into **the cup** until it was full
> She poured water from **the pitcher** into **the cup** until it was empty
>
> **The city council** refused **the women** a permit because they feared violence
> **The city council** refused **the women** a permit because they advocated violence

Winograd Schema, recently proposed as an alternative to the Turing test. If you've fully solved coreference, arguably you've solved AI.

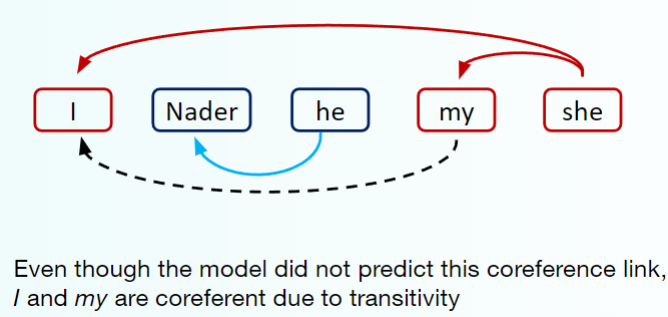
Mention Pair/Mention Ranking

Train a binary classifier that assigns every pair of mentions a probability of being coreferent. E.g., for "she" look at all candidate antecedents and decide which are coreferent with it. Positive $\Rightarrow P(m_i, m_j)$ near 1, while negative $\Rightarrow P(m_i, m_j)$ near 0.

Mention Pair Training N mentions in a document, $y_{ij} = 1$ if mentions m_i, m_j are coreferent, -1 otherwise. Just train with regular binary cross-entropy loss

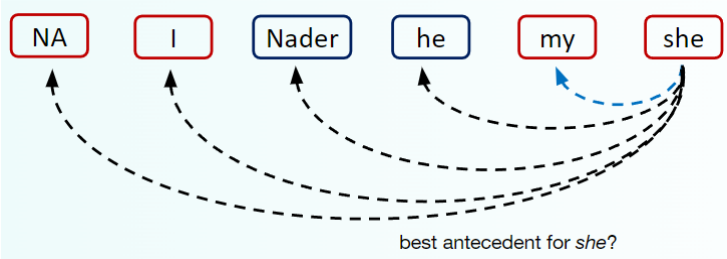
$$J = -\sum_{i=2}^{N}\sum_{j=1}^{i} y_{ij} p(m_j, m_i)$$

Mention Pair Prediction Coreference resolution is a clustering task, but we are only scoring pairs of mentions. What to do? Pick some threshold (e.g. 0.5) and add coreference links between mention pairs where $P(m_i, m_j)$ is above the threshold. Take the transitive closure to get the clustering.



Coreference Models

Mention Ranking Assign each mention its highest scoring candidate antecedent according to the model. Dummy NA mention allows model to decline linking the current mention to anything ("singleton" or "first" mention.



Training We want the current mention m_j to be linked to any one of the candidate antecedents it's coreferent with. Mathematically, we want to maximize the following probability

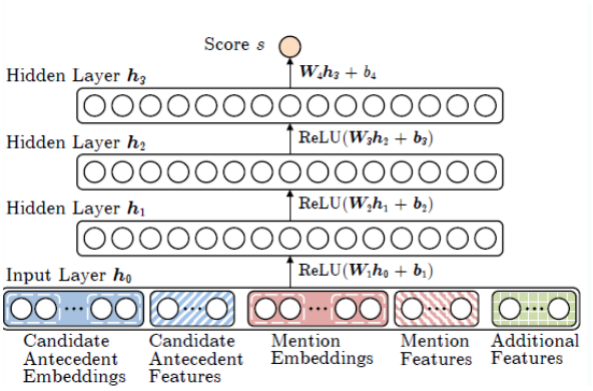
$$\sum_{j=1,i=1} 1(y_{ij} = 1)P(m_j, m_i)$$

iterating through candidate antecedents, for ones that are coreferent to m_j we want the model to assign a high probability.
The model could produce 0.9 probability for one of the correct antecedents, and low probability for everything else, and the sum will still be large.
How to compute the probabilities?

Non-Neural Statistical Classifier. Features that has to be considered:

- Person/Number/Gender agreement
- Semantic compatibility
- Certain syntactic constraints
- More recently mentioned entities are preferred
- Grammatical role, prefer entities in the subject position
- Parallelism

Simple Neural Network. Standard FFNN, with word embeddings and few categorical features as input layer. Embeddings: previous two words, first word, last word, head word... of each mention. Still need some other features: distance, document genre, speaker information...



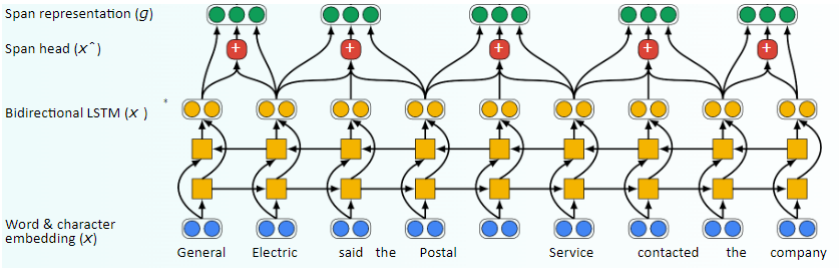
More advanced models using LSTMs, attention, transformers...

End-To-End Neural Coref Model Improves over simple FFNN with LSTM, and attention. It does mention detection and coreference end-to-end: no mention detection step, instead considers every span of text of up to a certain length as a candidate mention (span = contiguous sequence of words).
The model is composed of:

First embed the words in the document using a word embedding matrix and a character-level CNN

Then run a bidirectional LSTM over the document

Next represent each span of text i going from START(i) to END(i) as a vector



$\hat{x}_i$ is an attention-weighted average of the word embeddings in the span.

Attention scores

$$\alpha_t = W_\alpha \cdot \text{FFNN}_\alpha(x_t^*)$$

dot product of weight vector and transformed hidden state

Attention distribution

$$a_{ij} = \frac{e^{\alpha_t}}{\sum_{k=\text{START}(i)}^{\text{END}(i)} e^{\alpha_k}}$$

just a softmax over attention scores for the span

Final Representation

$$\hat{x}_i = \sum_{k=\text{START}(i)}^{\text{END}(i)} a_{ij} x_t$$

attention-weighted sum of word embeddings

The vector that represents the span of text is

$$g_i = [x_{\text{START}(i)}, x_{\text{END}(i)}, \hat{x}_i, \phi(i)]$$

which contains

$x_{\text{START}(i)}, x_{\text{END}(i)}$ the hidden states for span's start and end, representing the context to the left and right of the span

$\hat{x}_i$ attention-based representation, which represents the span itself

$\phi(i)$ additional features, which represents other information not in the text

Lastly, score every pair of spans to decide if they are coreferent mentions

$$s(i,j) = s_m(i) + s_m(j) + s_a(i,j)$$

Scoring functions take the span representation as input

$s(i,j)$ = are spans i and j coreferent mentions?

$s_m(x) = W_m \cdot \text{FFNN}(g_x)$ = is x a mention?

$s_a(i,j) = W_a \cdot \text{FFNN}([g_i, g_j, g_i \cdot g_j, \phi(i,j)])$ = do they look coreferent? $g_i \cdot g_j$ to include multiplicative interactions between the representations, and again with $\phi(i,j)$ we include some extra features.
It's intractable to score every pair of spans: $O(T^2)$ spans of text in a document with T words, meaning $O(T^4)$ runtime. So we have to do lots of pruning to make it work, only considering a few of the spans that are likely to be mentions. Attention learns which words are important in a mention, a bit like head words.

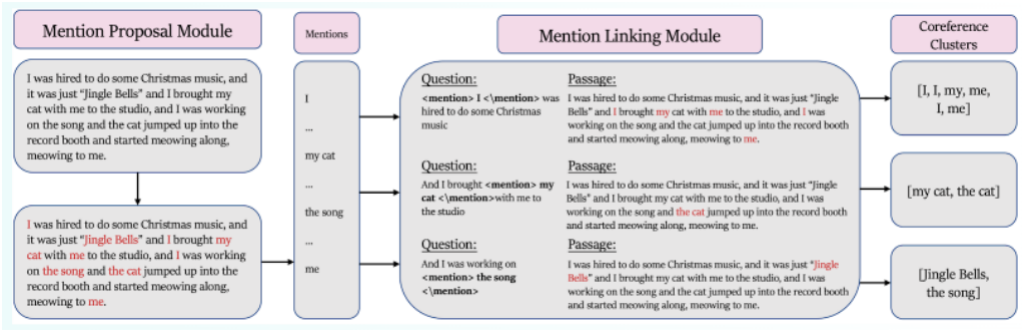
BERT-based coref: now has the best results Pretrained transformers can learn long-distance semantic dependencies in text

Span-BERT: pretrains BERT models to be better at span-based prediction tasks like coref and question answering

BERT-QA for coref, treat coreference like a deep question answering task: "points to" a mention and asks "what is its coreferent?", answer span is a coreference link.

Maybe you don't have to do it with spans after all, and you can go back to a representation of a word (maybe the head) and make things $O(T^2)$

CorefQA



1. The input passage is fed into the **Mention Proposal Module** to obtain candidate mentions
2. The **Mention Linking Module** is used to extract coreferent mentions from the passage for each proposed mention
3. The coreference clusters are obtained using the scores produced in the above two stages

Mention Proposal Consider all span up to a given length and prune the candidate spans greedily during both training and evaluation. The mention score is

$$s_m(i) = \text{FFNN}_m([x_{\text{FIRST}(i)}, x_{\text{LAST}(i)}])$$

Mention Linking Use the question answering framework to compute $s_a(i,j)$. Transformer input triple: {context, query, answers} $= \{X, q, a\}$

X context: input document

$q(e_i)$ query: sentence containing e_i replace by <mention> e_i </mention>

a answers: coreferent mentions of e_i

IOB tagging for mention words

$$p_i^{tag} = \text{Softmax}(\text{FFNN}_{tag}(x_i))$$

Anaphora score

$$s_a(j \mid i) = \frac{1}{|e_j|}\left(\log p^B_{\text{FIRST}_{(j)}} + \sum_{k=\text{FIRST}_{(j)+1}}^{\text{LAST}_{(j)}} \log p^I_k\right)$$

The overall score is

$$s(i,j) = s_m(i) + s_m(j) + s_a(i,j)$$

Mention Pruning Number of mention pairs is intractable, $O(n^4)$. For each query $q(e_i)$ collect only C span candidates based on the $s_a(j \mid i)$ scores.

Coreference Evaluation Many different metrics: MUC, CEAF, LEA, B-CUBED, BLANC... people often report the average over a few different metrics. Essentially, the metrics think of coreference as a clustering task and evaluate the quality of the clustering.

B-CUBED For each mention, compute a precision and a recall, and average them.

0.19 Integrating Knowledge in Language Models

Recap Standard LMs predict the next word in a sequence of text and can compute the probability of a sequence. Alternatively, masked LMs (e.g. BERT) predict a masked token in a sequence of text using bidirectional context. Both types can be trained over huge amounts of unlabeled text!
Traditionally LMs are used for many tasks involving generating or evaluating the probability of text. Recently, LMs are commonly used to generate pretrained representations of text that encode some notion of language understanding for downstream NLP tasks. **Can a LM be used as a knowledgebase?**

Eliciting Knowledge Prompting can be used to direct LM towards an answer: often the answers look plausible but are incorrect. Alternatively, one can use the LM to extract an answer from text by a reliable source.
Predictions generally makes sens but are not all factually correct. Why?

Unseen facts: some facts may not have occurred in the training corpora

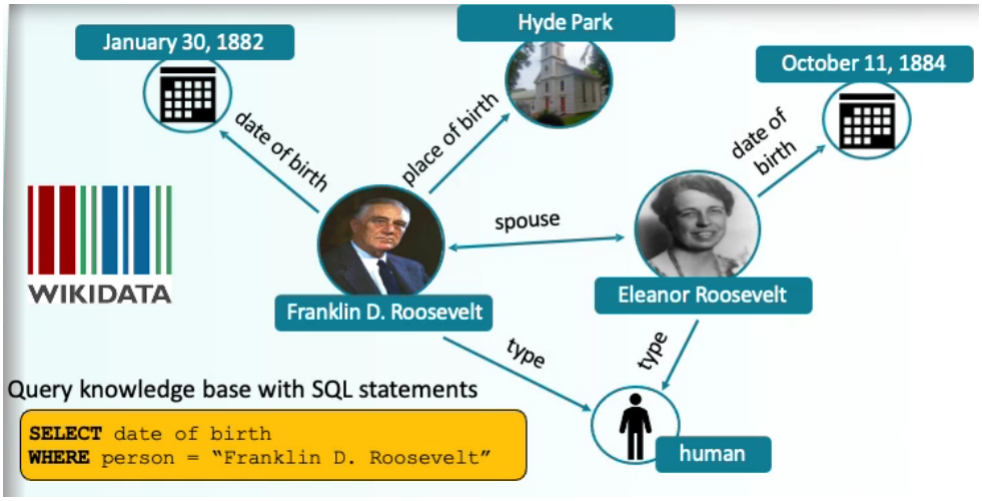
Rare facts: LM hasn't seen enough examples during training to memorize the fact

Model sensitivity: LM may have seen the fact during training, but is sensitive to the phrasing of the prompt (e.e. "made" instead of "created")

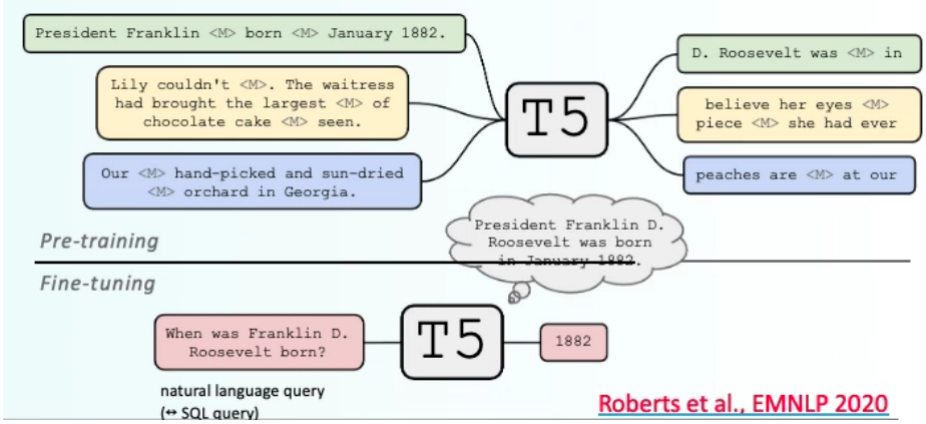
LMs have some knowledge but **fail to reliably recall knowledge**, a serious challenge.

Knowledge-aware LMs are important. LM pretrained representations can benefit downstream tasks that leverage knowledge. For instance, question answering and information extraction are easier with some knowledge of the entities involved. Stretch goal: can LMs ultimately replace traditional knowledgebases? Instead of querying a knowledge base for a fact, e.g. with SQL, query the LM with a natural language prompt. Of course this requires the LM to have high quality on recalling facts.

Querying Traditional Knowledgebases



Querying LM as Knowledgebases Pretrain LM over unsdtructured text and then query with natural language.



Advantages of LMs over traditional KBs LMs are pretrained over large amounts of unstructured and unlabeled text, while KBs require manual annotation or complex NLP pipelines to populate.
LMs support more flexible natural language queries, while traditional KBs would have more restricted ways of asking queries.
However, there are many open challenges:

Hard to interpret, i.e. why does the LM produce an answer

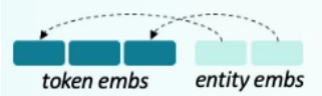
Hard to trust, i.e. the LM may produce a realistic but incorrect answer

Hard to modify, i.e. not easy to remove or update knowledge in the LM

0.19.1 Adding Knowledge to LMs

Add pretrained entity embeddings

ERNIE, QAGNN/GraseLM



Facts about the world are usually in terms of entities. Pretrained word embeddings do not have a notion of entities: different word embeddings for the same entity. What if we assign an ambedding per entity? **Single entity embedding**.
Goal: get pretrained entity embeddings that encode factual knowledge, and add to language model. To build entity embeddings, one needs to do **entity linking**.

Entity Linking Links mentions in text to entities in a knowledgebase. Entity linking tells us which entity embeddings are relevant to the text.

Entity embeddings are like word embeddings, but for entities in a knowledgebase. Many techniques:

Knowledge graphg mebieddings methods

Woerd-entity embeddings methods

transofrmer encodings of entity descriptions

Incorporate Entity Embeddings from a Different Embeddings Space Learn a **fusion layer** to combine context and embedding information

$$h_j = F(W_t w_j + E_w e_k + b)$$

With w_j embedding of word j in a sequence of words and e_k the corresponding entity embedding.
Intuition: there's an alignment between entities and words i nthe sentence, such that projections $W_t w_j$ and $W_e e_k$ are in the same vector space.

ERNIE Enhanced Language Representation with Informative Entities

Text encoder: multi-layer bidirectional transformer encoder over the words in the sentence

Knowledge encoder: stacked blocks composed of

Two multi-headed attentions (MHAs) over entity embeddings and token embeddings

A fusion layer to combine the output of the MHAs

Fusion representation:

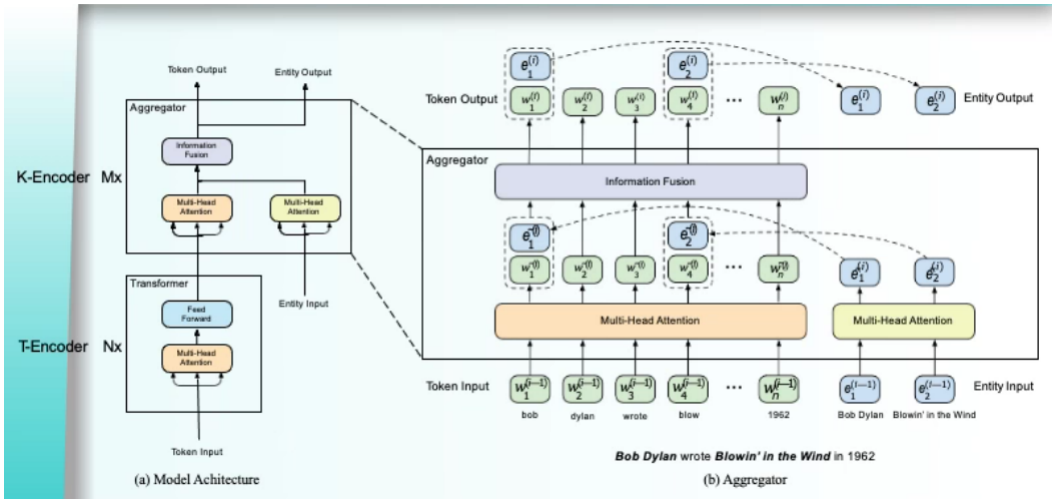
$$h_j^{(i)} = \sigma(\tilde{W}_t^{(i)} \tilde{w}_t^{(i)} + \tilde{W}_e^{(i)} \tilde{w}_e^{(i)} + \tilde{b}^{(i)})$$

Token embedding output, fed to next block:

$$w_j^{(i)} = \sigma(W_t^{(i)} h_j + b_t^{(i)})$$

Entity embedding output, fed to next block:

$$e_j^{(i)} = \sigma(W_e^{(i)} h_j + b_e^{(i)})$$



Pretrained with three tasks

Masked LM

Next sentence prediction

Knowledge pretraining task (dEA): randomly mask token-entity alignments and predict corresponding entity for a token from the entities in the sequence

$$p(e_j \mid w_i) = \frac{\exp(W w_i \cdot e_j)}{\sum_{k=1}^{m} \exp(W w_i \cdot e_k)}$$

$$f_{ERNIE} = f_{MLM} + f_{NSP} + f_{dEA}$$

Strenghts:

Combine entity and context info through fusion layers and knowledge pretraining task

Improves perormance downstream on knowledge-driven tasks

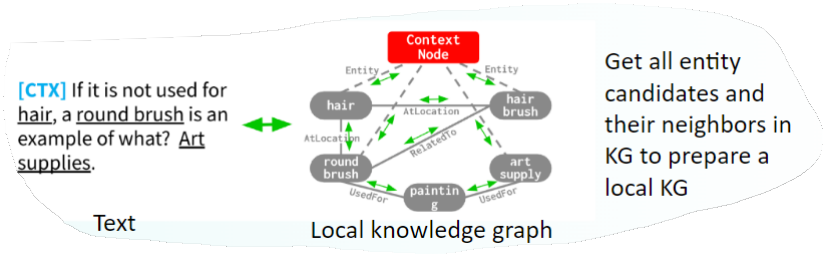
Limitations:

Needs text data with entities annotated as input, even for downstream tasks

It's challenging to get a good entity linker for any domain of text or tasks

Requires further (expensive) pretraineing of the LM

QAGNN/GreaseLM Key idea: when adding entity embeddings to LM, dynamically update them, together with neighbor or related entities, in **knowledge graph** as well as text.



Benefits:

Robust to non-perfect entity linking: can include all entity candidates and let the model figure out what to use

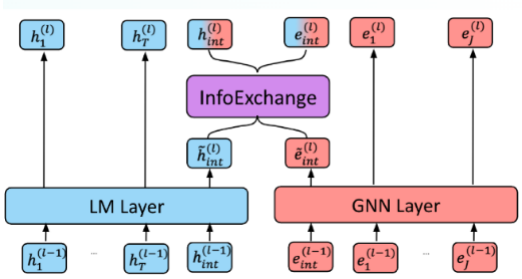
Better contextualize knowledge: helpful for joint reasoning about text and knowledge (e.g. QA tasks)

A **Graph Neural Network** (**GNN**) is a neural network designed for encoding graph data. It updates each node representation by aggregating message vectors from neighbor nodes.

$$a_k^{(v)} = \text{Aggregate}^{(k)}\left(\left\{h_u^{(k-1)} \mid u \in N(v)\right\}\right)$$

$$h_v^{(k)} = \text{Combine}^{(k)}\left(h_v^{(k-1)}, a_v^{(k)}\right)$$

The text is encoded by a LM, the knowledge graph (KG) is encoded by a GNN and they are fused together for multiple rounds.



QAGNN and GreaseLM outperform previous BERT-based models on knowledge-intensive question answering tasks.

Use an external memory

KGLM

Previous methods rely on the pretrained entity embeddings to encode the factual knowledge from KBs for the language model. Are there more direct ways than pretrained entity embeddings to provide the model factual knowledge? Yes, give the model access to an external memory (a key-value store for KG triples or facts) in a ways that is independent of learned model parameters.
Advantages: can directly update facts in the extrnal memory without re-training the model, also interpretable because it's more visible which fact in external memory the LM used to make prediction (it's hard to debug model prediction if we use entity embeddings).

KGLM Key idea: condition the language model on knowledge graph (KG).
The LM predict the next word computing ($x^{(1)}, \ldots, x^{(t)}$ is a sequence of words)

$$P(x^{(t+1)} \mid x^{(t)}, \ldots, x^{(1)})$$

Goal: **predict** the next word **using entity information** by computing ($\epsilon^{(t)}$ is the set of KG entities mentioned at timestep t)

$$P(x^{(t+1)}, \epsilon^{(t+1)} \mid x^{(t)}, \ldots, x^{(1)}, \epsilon^{(t)}, \ldots, \epsilon^{(1)})$$

Builds a "local" KG as it iterates over the sequence. Local KG is a subset of the full KG with only the entities relevant to the sequence so far. Can provide a strong signal for predicting what comes as the next word. When should the LM use the local KG to predict the next word?
First, use the LSTM hidden state to predict the type of the next word: related entity (in the local KG), new entity (not in the local KG) or not an entity.

> **Related entity**: find the top-scoring parent and relation in the local KG using the LSTM hidden state and pretrained entity and relation embeddings.
> $P(p_t) = \text{Softmax}(v_p h_t)$ where p_t is the "parent" entity, v_p is the corresponding entity embedding and h_t is from the LSTM hidden state. Similarly for predicting top relation.
> New entity: tail entity from KG triple of (top parent entity, top relation, tail entity)
> Next word: most likely next token over vocabulary expanded to include the tail entity and its aliases
>
> **New entity**: find the top-scoring entity in the full KG using the LSTM hidden state and pretrained entity embeddings.
> Next entity: directly predict top-scoring entity
> Next word: most likely next token over vocabulary + entity aliases
>
> **Not an entity**
> Next entity: none
> Next word: most likely next token over standard vocabulary

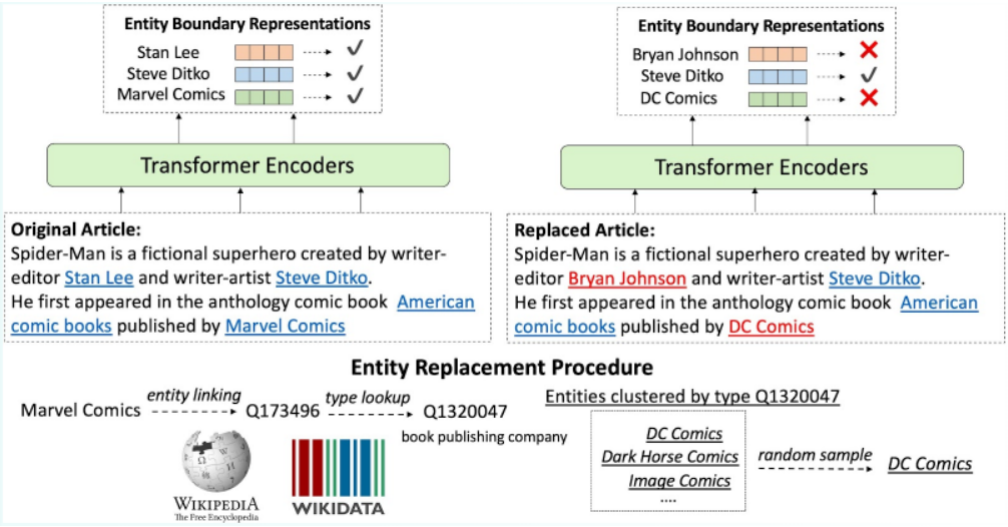
It supports modify/updating facts.

Modify Pretrained Data

WKLM, ERNIE, Salient Span Masking

Previous methods incorporated knowledge explicitly through pretrained embeddings and/or external memory. Can knowledge also be incorporated implicitly through unstructured text? Yes, mask or corrupt the data to introduce additional training tasks that require factual knowledge.
Advantages: no additional memory/computation, no modifications to the architecture.

WKLM Key idea: train the model to distinguish between true and false knowledge. Replace mentions in the text with mentions that refer to different entities of the same type, to create negative knowledge statements. Model predicts whether entity has been replaced or not. Type-constraint is used to enforce linguistcally correct sentences, otherwise the model may trivially predict "replaced" using linguistic signal instead of knowledge.



Trained using an **entity replacement loss**, to train the model in distinguishing between true and false mentions

$$L_{entRep} = 1_{e \in E^+} \log P(e \mid C) + (1 - 1_{e \in E^+}) \log(1 - P(e \mid C))$$

with e entity, C context and E^+ represent a true entity mention.
The total loss is the combination of standard masked language model loss (MLM) and the entity replacement loss. MLM is defined at the token-level, while entRep is defined at the entity-level. Treating a whole entity (could be multi-word) instead of a token as one unit can make LMs more knowledge-aware.

Inductive Biases Through Masking

Can we encourage the LM to learn factual knowledge by clever masking? A thread in recent works.

ERNIE

Salient span masking Outperforms other masking/corruption strategies on retrieval and QA tasks.

0.19.2 Evaluation on Downstream Tasks

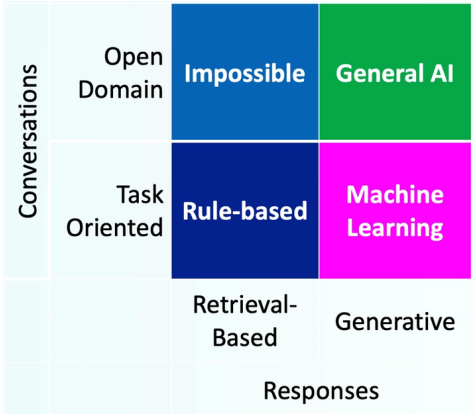
Knowledge-Intensive Downstream Tasks Measures how well the knowledge-enhanced LM transfers its knowledge to downstream tasks. Unlike probes, this evaluation usually involves finetuning the LM on downstream tasks, like evaluating BERT on GLUE tasks. Common knowledge-intensive tasks are: relation extraction, entity typing, question answering.

0.20 Dialogue Systems

Chatbots are a very challenging application of all the elements we've seen so far: from tokenization, to question answering, to learning, to information retrieval...

Early Approaches ELIZA, 1966: used clever hand-written templates to generate replies that resembled the user's input utterances. Several programming frameworks available today for building dialog agents, Google Assistant, Amazon Alexa...

Templates and Rules Hand-written rules to generate replies and simple pattern-matching or keyword retrieval techniques are employed to handle the user's input utterances. Rules are used to transform a matching patter or keyword into a reply.



Open Domain (harder)

The user can take the conversation anywhere

No necessarily a well-defined goal or intention

conversations on social media sites like Twitter and Reddit are typically open domain

Task Oriented (easier)

The space of possible inputs and outputs is somewhat limited

The system is trying to achieve a very specific goal

Technical customer support or shopping assistants are examples of closed domain problems

Retrieval Based (easier)

Use a repository of predefined response and some heuristics to pick an appropriate response based on the input and context

The heuristic could be as simple as rule-based expression match, or as complex as an ensemble of ML classifiers

These systems don't generate any new text, they just pick a response from a fixed set

No grammatical mistakes

Unable to handle unseen cases

Can't refer back to contextual entity information like names mentioned earlier in the conversation

Generative (harder)

Don't rely on predefined responses

Generate new response from scratch

Generative models typically based on transducer techniques

They "transduce" an input into an output (response)

Can refer back to entities and give the impression of a talking person

Hard to train

Likely to make grammatical mistakes, especially on longer sentences

Typically require huge amount of training data

Short Conversation (easier)

Goal: create a single response to a single input
E.g.: answering a specific question from a user with an appropriate answer

Long Conversation (harder)

Bot goes through multiple turns and must keep track of what has been said

Alexa Prize Challenge aims at building a socialbot capable of engaging users for 20 minutes

0.20.1 Task-Oriented

Task-oriented dialogue systems interact with a user in order to complete a specific task.

Must understand the dialogue context

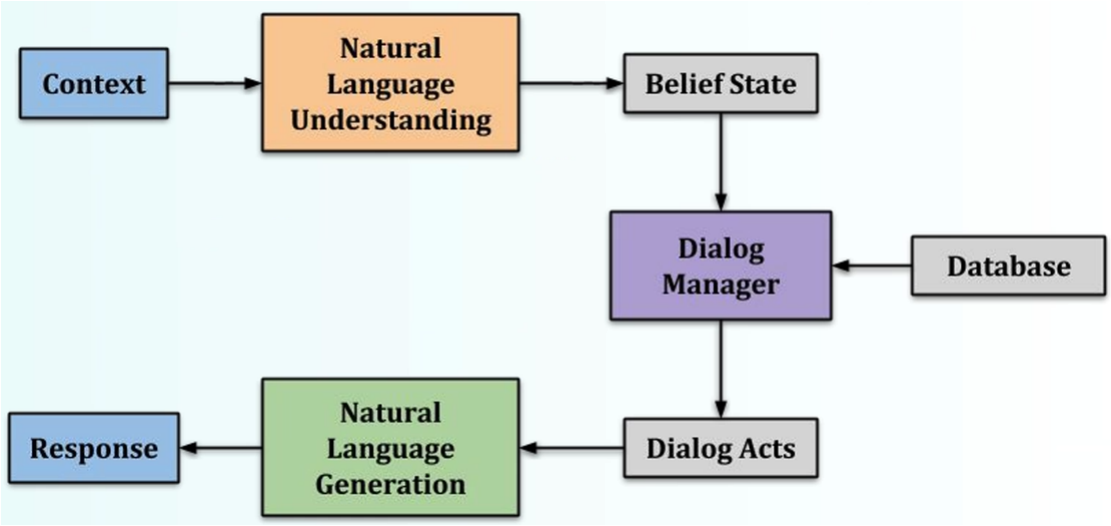
Must track belief state over dialogue context

Often need to interpret structured database output

Must follow task-specific dialogue policy

Must generate natural language responses

A possible pipeline is



Natural Language Understanding It involves several key tasks

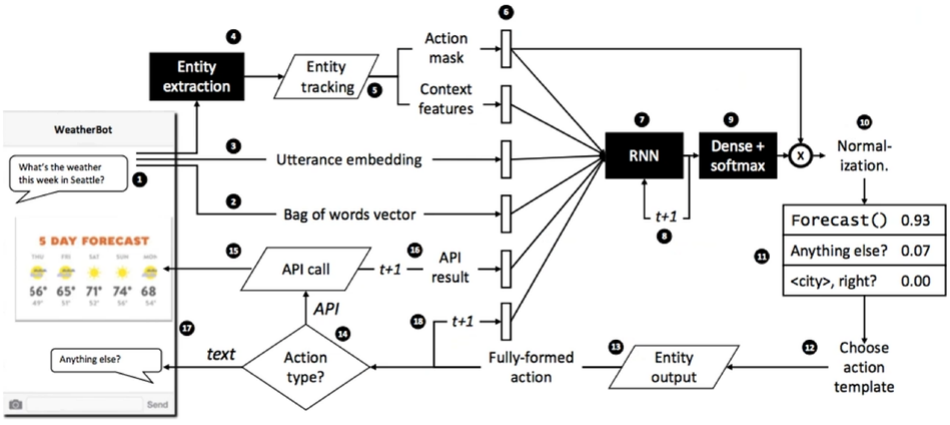
Intent Prediction: what is the user's intent/goal

Slot Filling: what are the slot values (e.g. what is the time)

State Tracking: track user information/goals throughout the dialogue

Tag	Sys	User	Description
HELLO($a=x, b=y, \ldots$)	✓	✓	Open a dialogue and give info $a=x, b=y, \ldots$
INFORM($a=x, b=y, \ldots$)	✓	✓	Give info $a=x, b=y, \ldots$
REQUEST($a, b=x, \ldots$)	✓	✓	Request value for a given $b=x, \ldots$
REQALTS($a=x, \ldots$)	χ	✓	Request alternative with $a=x, \ldots$
CONFIRM($a=x, b=y, \ldots$)	✓	✓	Explicitly confirm $a=x, b=y, \ldots$
CONFREQ($a=x, \ldots, d$)	✓	χ	Implicitly confirm $a=x, \ldots$ and request value of d
SELECT($a=x, a=y$)	✓	χ	Implicitly confirm $a=x, \ldots$ and request value of d
AFFIRM($a=x, b=y, \ldots$)	✓	✓	Affirm and give further info $a=x, b=y, \ldots$
NEGATE($a=x$)	χ	✓	Negate and give corrected value $a=x$
DENY($a=x$)	χ	✓	Deny that $a=x$
BYE()	✓	✓	Close a dialogue

Dialogue Manager Controls the architecture and structure of dialogue.
Takes input from ASR (speech recognizer) and NLU components, maintains belief/dialogue state (some sort of internal state). Iterfaces with database and passes output to natural language generation/text-to-speech modules.
Can train an LSTM that takes in text and entities and directly chooses an action to take (reply or API call). Trained using a combination of supervised and reinforcement learning.



Dialogue State It consists of all the information given so far, including user-specified constraints on the slots.

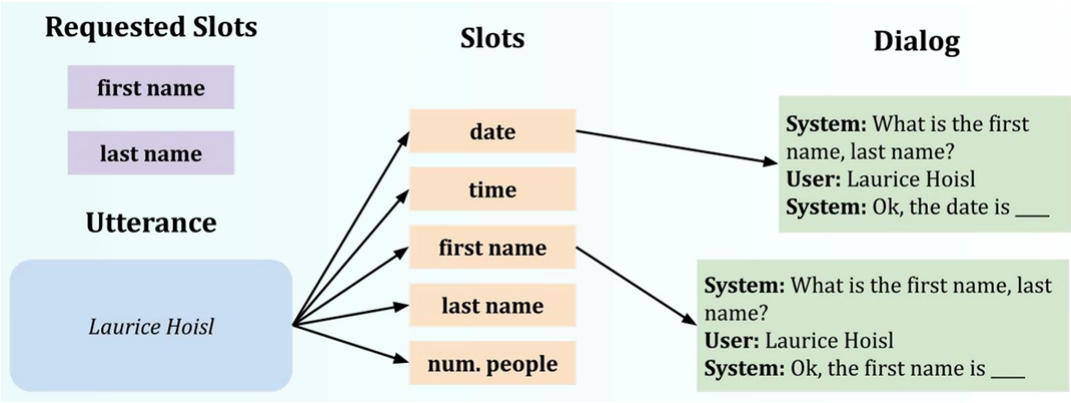
Dialogue Act Labeling and Slot Filling Given an user utterance, the system needs to identify

The dialogue act label

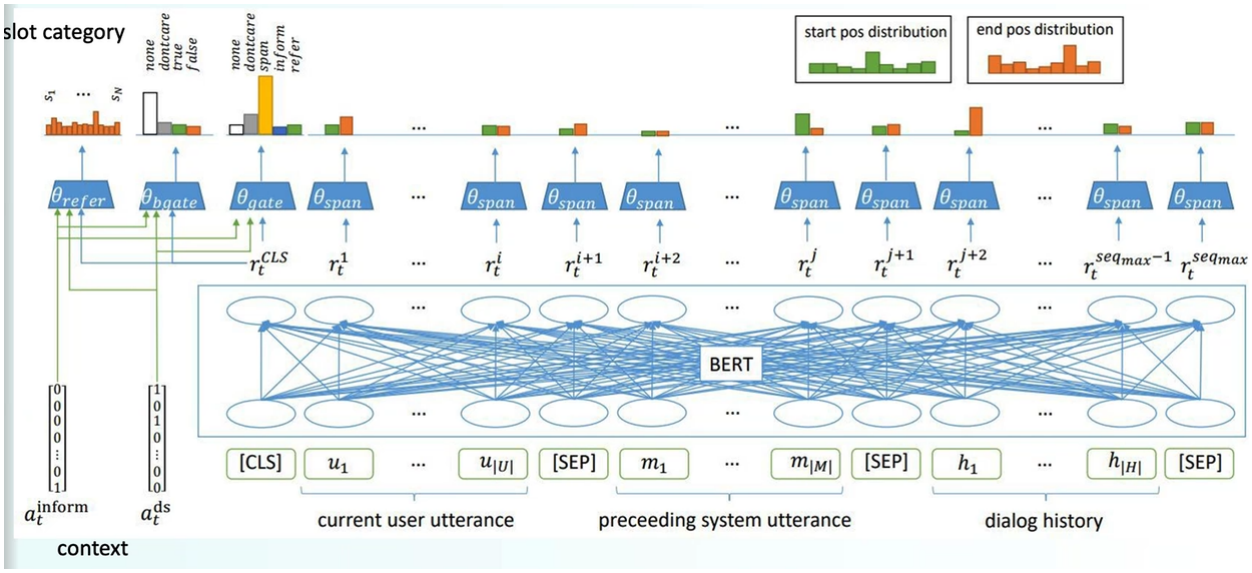
The slots that are being filled/constrained

Slot Filling with ConVEx Pre-training paradigm specifically for slot filling, with strong few-shot/zero-shot performance.
We have template sentences with the mask BLANK on some of the words and input sentences with the slot value present (and highlighted, e.g. in bold)

DialoGPT Continue pre-training GPT-2 on conversations from Reddit, filtering: long utterances, non-English utterances, URLs and toxic comments. Train on 174M dialogue instances (1.8B words).
Human-level response generation ability.
GenSF adapts pre-trained DialoGPT model to the slot filling task.

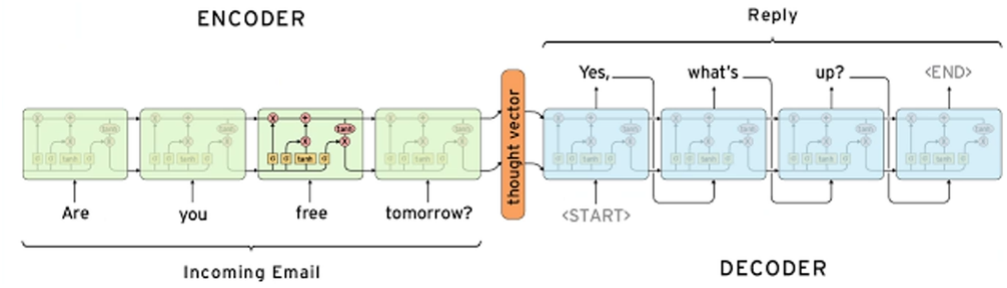


TripPy



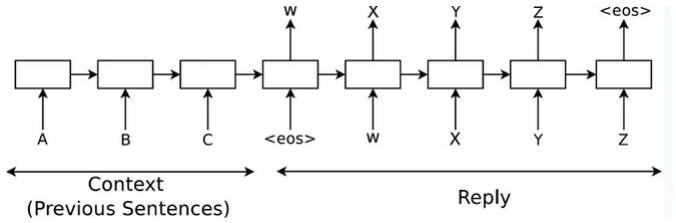
0.20.2 Generation-Oriented

Transducer Model Train machine translation system to perform translation from utterance to response.



Neural Models for Dialogue Response Generation Like other translation tasks, dialogue response generation can be done with encoder-decoders.

Seq2Seq Used even before transformers and attention were invented.

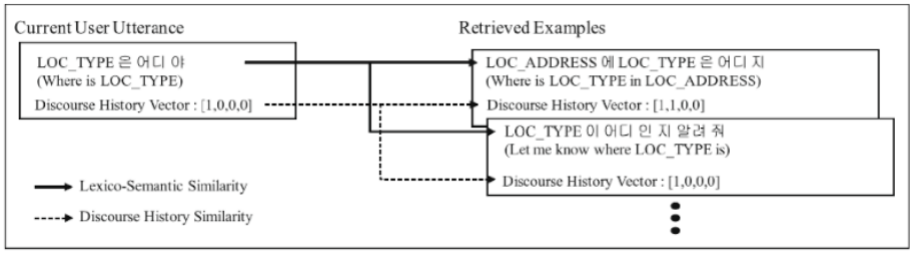


0.20.3 Retrieval-Based

Most system today rely on retrieval

Templates Many requests can be answered with templates. Select the most relevant response from a collection of templates, determine the slots required to fill it and instantiate the template with those values. Slots filler can be extracted from user utterance or retrieved with a query.

Retrieval-Based Chat Basic idea: given an utterance, find the most similar in the database and return it.



Similarity based on **exact word match plus extracted features** regarding discourse.

Neural Response Retrieval Idea: use neural models to soften the connection between input and output and do more flexible matching.

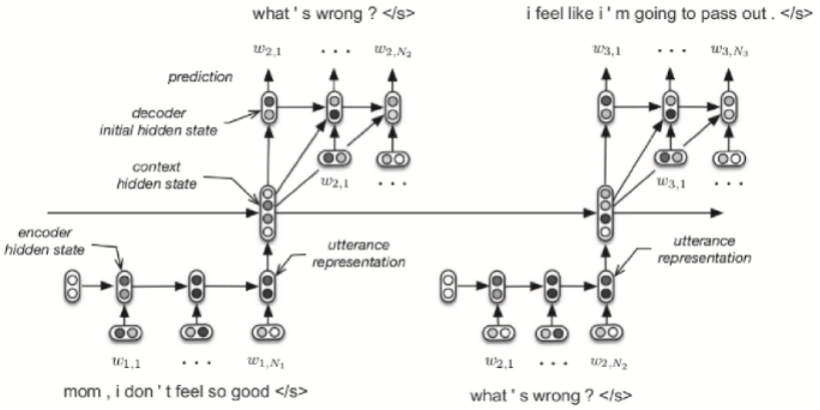
sim	Sentences	Matrix
0.94	S_1) Captain, we can not keep going fast on these icy roads. S_2) We can not keep going fast on these icy roads!	
0.60	S_1) Hold your fire! He's got a girl. S_2) Looks like he's got a hostage.	
0.38	S_1) Yes, I can see that too and I don't think it's so terrible. S_2) That's why I do all the thinking.	

0.20.4 Challenges

Four main challenges: incorporating context, coherence, diversity, personality.

Incorporating Context To produce sensible response systems may need to **incorporate both linguistic and physical context**. In long dialogues, people keep track of what has been said and what information has been exchanged. Some experiments try to embed a conversation into vectors.

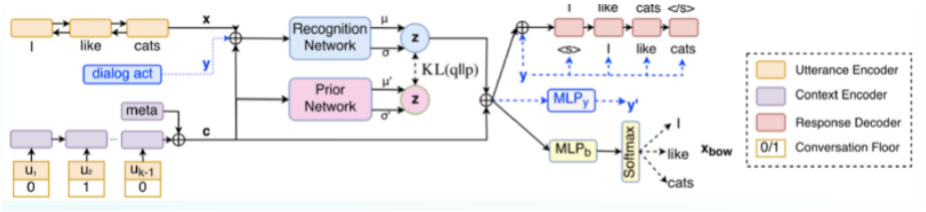
Coherence Considering only a single previous utterance will lead to local coherence but global incoherence: **need to consider more context**. Contrast to MT, where context sometimes is helpful and sometimes isn't.
A simple solution is to **concatenate utterances**: some works consider one additional previous context utterance concatenated together, while other works just concatenate together all previous utterances and hope for the best.
Or a **hierarchical encoder-decoder model**: also have utterance-level RNN track overall dialogue state (2RNN for words, RNN for utterance, no attention).



Diversity For translation, there is lexical variation but content remains. We want to avoid providing always the same answer with the same words. We desire more varied responses.

Input: What are you doing?	
−0.86 I don't know.	−1.09 Get out of here.
−1.03 I don't know!	−1.09 I'm going home.
−1.06 Nothing.	−1.09 Oh my god!
−1.09 Get out of the way.	−1.10 I'm talking to you.
Input: what is your name?	
−0.91 I don't know.	...
−0.92 I don't know!	−1.55 My name is Robert.
−0.92 I don't know, sir.	−1.58 My name is John.
−0.97 Oh, my god!	−1.59 My name's John.
Input: How old are you?	
−0.79 I don't know.	...
−1.06 I'm fine.	−1.64 Twenty-five.
−1.17 I'm all right.	−1.66 Five.
−1.17 I'm not sure.	−1.71 Eight.

Discourse-level Variable Autoencoder: encode **entire previous dialog context** as latent variable in VAE, also meta information such as dialog acts.



Diversity Promoting Objective: to mitigate the dull response system ("*I don't know*"), a diversity-promoting objective function has been proposed:

Use **MMI** (**Maximum Mutual Information**) rather than cross-entropy, as a loss function

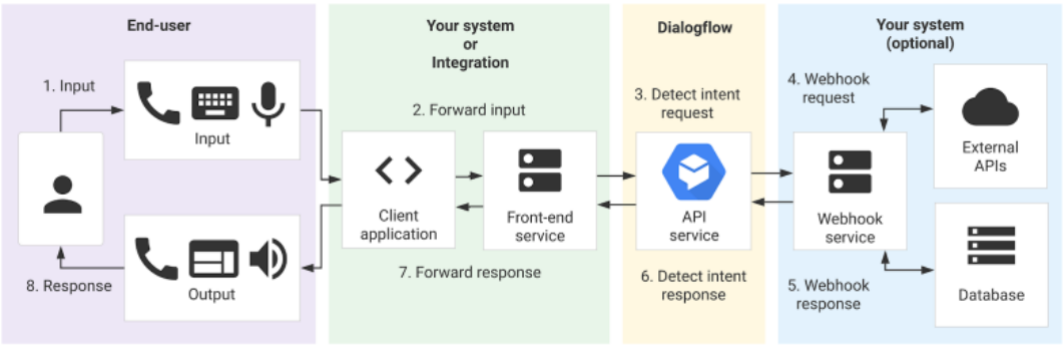
Penalize high-likelihood responses (anti-LM objective)

Basic idea: we want responses that are likely given the context, unlikely otherwise. Method: subtract weighted unconditioned log probability from conditioned probability.

Personality If we train on all of our data, our agent will be a mish-mash of personalities. We would like our agents to be consistent.
Personality infused dialogue can address this. Train a generation system with controllable "knobs" based on personality traits, e.g. extraversion. Non-neural approach, but well done and perhaps applicable.
Another idea is **speaker embeddings**, that may learn general facts associated with the specific speaker, e.g.: to the question "*Where do you live?*" it might reply with different answers depending on the speaker embedding.

0.20.5 Google DialogFlow

DialogFlow is a natural language understanding platform for designing conversational user interfaces. It generates automatically annotated templates from examples of training phrases that contain parts that can be matched to an existing entity type.



Some key concepts:

Agent: handles conversations with end-users, they can request your Action by typing or speaking to the Assistant

Intent: an underlying goal or task the user wants to do, e.g. ordering coffee. Each agent may have many intents, and when a user says something, DialogFlow matches the user expression to the best intent

Entity: each intent parameter has a type, called the entity type, which dictates exactly how data from an end-user expression is extracted

Flows: are used to define the topics in a conversation and the associated conversational paths

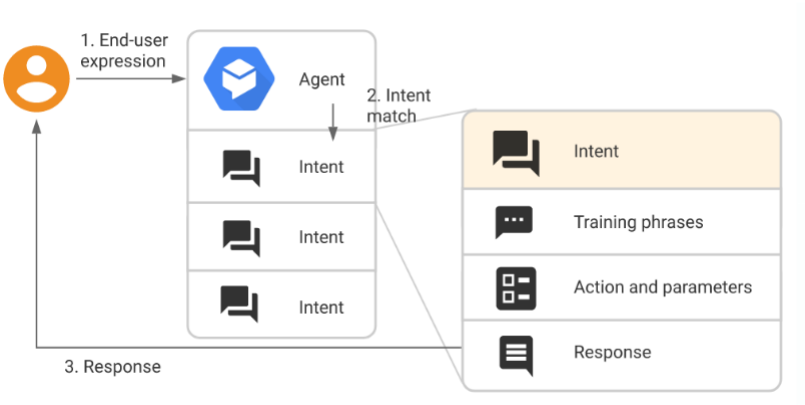
Page: a conversation can be described and visualized as a state machine, where the states of a session are represented by pages

Fulfillment: service, app, feed, conversation or other logic that handles an intent and carries out the corresponding Action

Webhook: services that host the business logic

Handler: used to control the conversation by creating responses for end-users and/or by transitioning the current page

Flow A basic flow is the following



Intent A basic intent contains the following

Training phrases: example phrases for what the user might say.
When an user expression resembles one of these phrases, DialogFlow matches the intent.

Actions: you can define an action for each intent.
When an intent is matched, DialogGlow provides the action to your system, and you can use the action to trigger certain actions defined in your system.

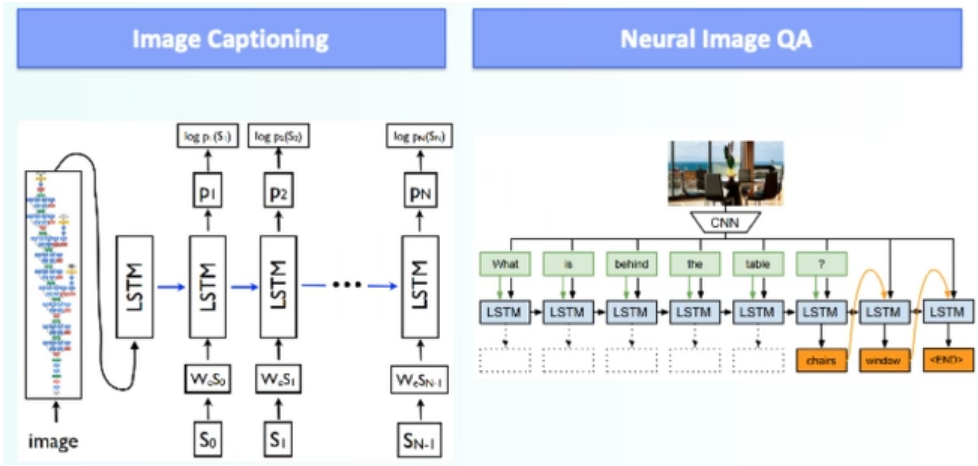
Parameters: when an intent is matched at runtime, DialogFlow provides the extracted values from the end-user expression as parameters, which are structured data.

Follow-Up Intents to automatically set contexts for pairs of intents.
A follow-up intent is a child of its associated parent intent.

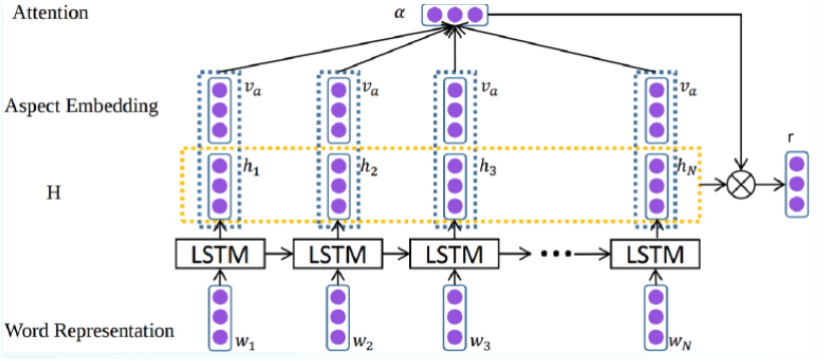
When a fulfillment for an intent is enabled, DialogFlow responds to that intent by calling a service that you define.

0.21 Trends and Future of NLP

Applications



Attention Mechanism Applied to NMT, effective in aspect based sentiment/topic classification and other tasks.



Story of recent years in Deep Learning NLP General representation learning recipe:

Convert your data into sequence of integers

Define a loss function to maximize data likelohood or create a denoising auto encoder loss

Train on *lots* of data

GPT-3: few-shot learning. Prompt the system with the model being able to somehow mimic the behavior of the task expressed by the prompt.
DALL-E: text-to-image model with impressive zero-shot generalization.
We discussed prompting:

Zero-shot: no supervised training data. Ask LM to generate from a prompt.

Reading comprehension: give context, question and wait for answer.

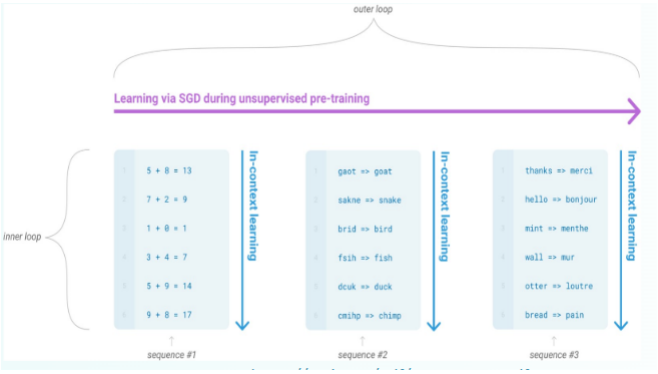
Summarization: give article and wait for summary.

Translation: few example of sentences pair, provide source sentence and wait for translation.

Question answering: give question and wait for answer.

We discussed model reuse: fine tuning, zero/few-shot learning and prompt tuning.

Large Language Models and GPT-3 175B parameters: 96 layers, 96 heads and 128 dimension heads. Same architecture as GPT-2 with the exception of locally banded sparse attention patterns, trained on 500B tokens from Wikipedia. Better than other models at language modeling and related tasks such as story completion.
Possesses flexible "in-context" learning: GPT-3 demonstrates some level of fast adaption to completely new tasks, happening via "in-context" learning.



The LM training (outer loop) is learning how to learn from the context (inner loop)

GPT-3 is only available via an inference API. Many interesting applications that demonstrate its flexible few-shot learning abilities, e.g.: natural language to Bash, databases in natural language, blending concepts...
It has some limitations: seems to do poorly on more structured problems that involve decomposing into atomic/primitive skills (RTE, arithmetic, word problems, analogy making...), doesn't seem to exhibit human-like generalization (systematicity).

0.21.1 Compositional Representations and Systematic Generalization

Systematicity Ability to produce/understand sentences is intrinsically connected to the ability/produce certain others. This means that there's a "definite and predictable pattern among the sentences we understand".

Compositionality Closely related to the idea of systematicity. "The meaning of an expression is a function of the meaning of its parts".
A homomorphism from syntax (structure) to semantics (meaning). That is, meaning of the whole is a function of immediate constituents (described by syntax).
E.g.: red rabbit: notion of red objects and notion of rabbit.

Compositionaliyy of representations is a helpful prior that could lead to systematicity in behavior. Questions:

> Are neural representations compositional?
>
> Do neural networks generalize systematically?

Tree Reconstruction Error (TRE): Compositionality of representations is about how well the representation approximates an explicitly homomorphic function in a learnt representation space.

0.21.2 Assessing Deep Learning for NLP

Neural Network Effectiveness It's wild that any of our model work at all. Their behavior is an emergent property of data and our design decisions. Accuracy on a held out test set is not sufficient to fully characterize them.

Understanding Models by Breaking Them Are our models robust to innocuous changes in their input? By robust, in this case we mean their outputs don't change. For example, if a QA model behaves well but changes answer when presented with a new, irrelevant sentence, the correct interpretation is that the model is not really working. This applies to other changes like contractions (e.g. "what's" instead of "what has") and the like.

Remarks

> Neural Models are complex, fascinating objects that **we don't currently understand**, but we're making strides to understand them better
>
> A wide variety of analysis methods have been developed for:
>
> > understanding a model's behavior on specific phenomena
> >
> > understanding what a model learns about a topic or task
> >
> > understanding what seemingly innocuous input changes make a model fail
> >
> > many other things, more every day

0.21.3 Inferring From Memory

Current State Transformer models have become quite popular and used everywhere. Neural methods are leading to a renaissance for all language generation tasks (i.e.: MT, dialogue, QA, summarizations...)
Real scientific question of whether we need explicit, localist language and knowledge representations and inferential mechanisms.

Memory and Inference Still have very primitive methods for building and accessing memories or knowledge. Current models have almost nothing for developing and executing goals and plans. Difficult to collect and count.

Inter-Sentence We still have inadequate abilities for understanding and using inter-sentential relationships. We still cant', at a large scale, do elaborations from a situation using commons sense knowledge but also having bias.

Limits of Single Task Learning Most models today are single task. Great performance improvements, but: projects starts from random, single unsupervised task can't fix it... we will never get to a truly general NLP model this way.

Multiple Tasks How to express different task in the same framework it's still very hard. The obstacle is **joint many-task learning**, which is hard:

Usually restricted to lower layers

Usually helps only if tasks are related

Often hurts performance if tasks are not related

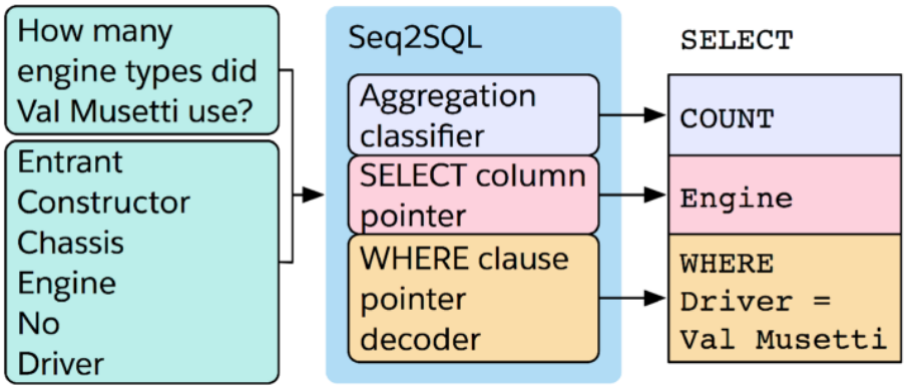
We lose powerful accuracy improvement techniques such as task-specific architecture and hyperparameter tuning

Deep Sequence Models RNNs are shown to be effective for a variety of language processing tasks. Somewhat surprisingly, these seemingly purely sequential models are very capable at modeling syntactic phenomena, and using them result in very strong dependency parsers for a variety of languages. Empirical evidence for their capabilities of learning the subject-verb agreement, relation in naturally occurring text, from relatively indirect supervision.

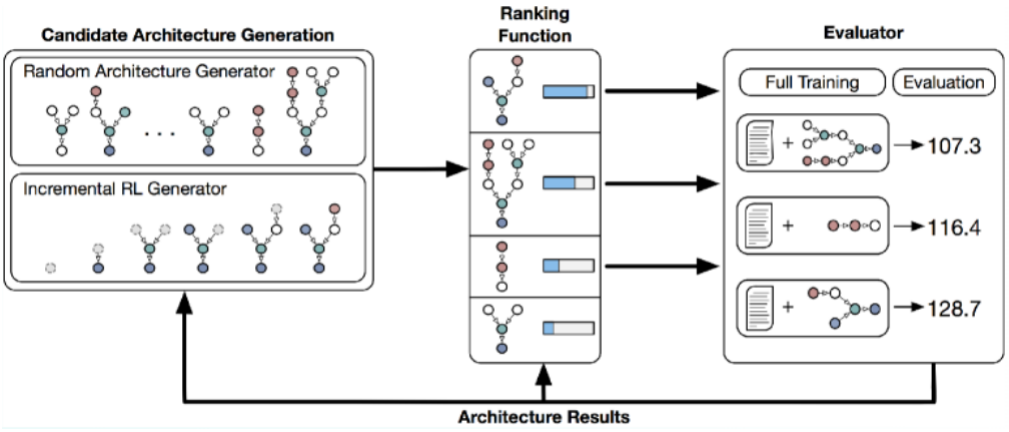
The 3 Equivalent NLP-Complete Super Tasks Language modeling, question answering and dialogue systems.

QA Completeness Every task may be recast as a QA task.
An obstacle: necessary inputs to QA. We need to **be able to understand text, images and databases** to really answer all kinds of questions.

Seq2SQL

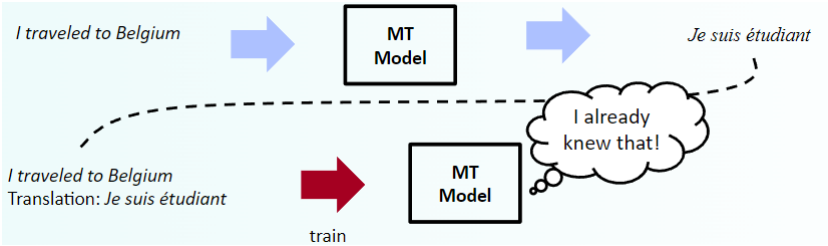


Another obstacle: architecture engineering. We don't yet know the right model architecture for comprehensive QA and joint multitask learning. Architecture search was an active area of research, but usually applied to simpler/known tasks...

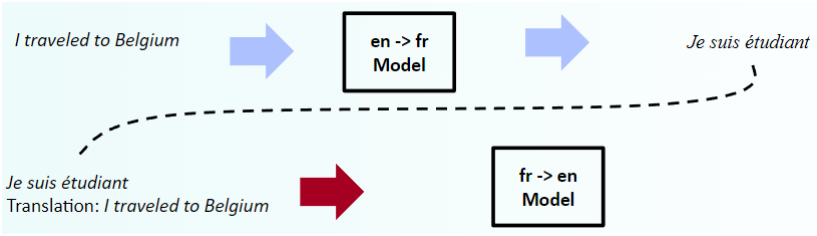


Also, difficult to obtain significant benefits from tree structure models: non GPU friendly, high sensitivity to parse errors.
Convolutional Reasoning without trees.

Machine Translation The problem with pre-training is that there's no interaction between the two languages during it.
Self-Training: label unlabeled data to get noisy training examples. Might be circular.



Back-Translation: have two machine translation models going in opposite directions. No longer circular, models never see "bad translations" but only bad inputs.



0.21.4 Huge Models

For several tasks, performance seems to increase with log(model size).

GPT-2 Reactions Pro-Release

> This model isn't much different from existing work
>
> Not long until these models are easy to train
>
> Photoshop
>
> Researchers should study this model to learn defenses
>
> Dangerous PR hype
>
> Reproducibility is crucial for science

Against-Release

> Danger of fake reviews, news comments. . . , but already done by companies and governments
>
> Precedent: "even if this model isn't dangerous, later ones might be"
>
> Smaller model still being released

Who should make these decisions? NLP experts, computer security experts, technology and society experts, ethics experts. . . ?
Need for more interdisciplinary science. Many other examples of NLP with big social ramifications, especially with regards to biases/fairness.

High Impact Decisions Growing interest in using NLP to help with high impact decision making: judicial decisions, hiring, grading tests. . .
Plus side: can quickly evaluate a machine learning system for some kinds of bias. However, machine learning reflects or even amplifies bias in training data, which could lead to the creation of even more biased data.

0.22 Thinking Fast and Slow

Two ways to make choices:

System 1: **fast**, intuitive, automatic thinking

All or thought and actions originate here
Simple, automatic, little to no effort, fast
Cognitive ease
Continuously assess situations
Continuously monitors thoughts
Intuition and creativity live here
Accepts all propositions as true
Need causal relationships to be able to make sense of environment
Categorizes events/things for quick recall

System 2: **slow**, rational, calculating thinking

Employed when things get difficult
Allocates attention and effort
Complex, effortful, reflective, slow
Assesses option with respect to goals
In charge of self control and behavior
Usually has the last word
Uncertainty and doubt live here

Systems 1 and 2 may explain the current dichotomy in approaches to AI:

Deep Learning for perceptive tasks (vision, language)

Symbolic or rule based formal systems for System 2 (planning and reasoning)

An important goal of AI research would be to overcome this dichotomy.