Project

- Presentations next week:

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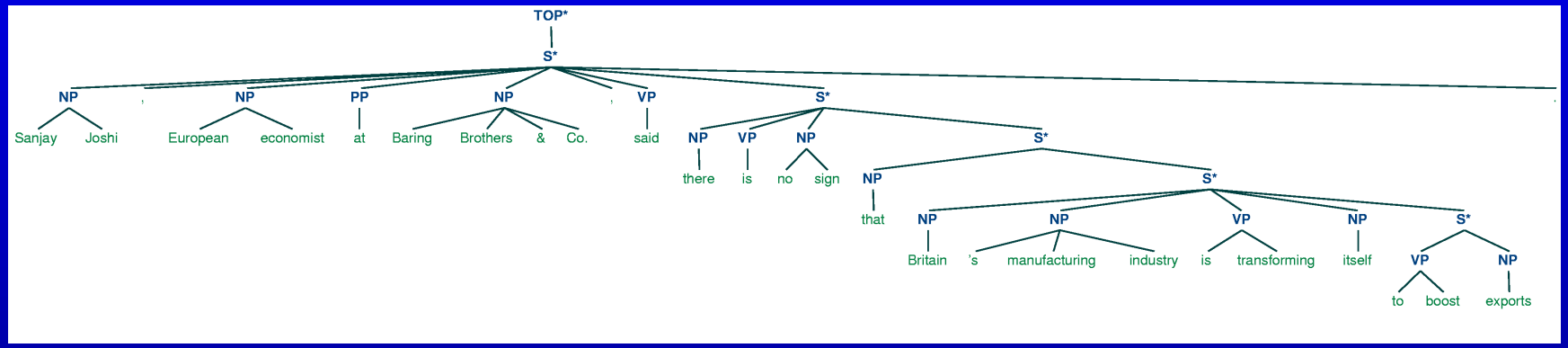
- Final project due: Wednesday, May 13 @ 5:00pm

- Turn in a *paper* explaining what you did, how well it worked, why it worked as well as it did but not better, etc., plus any *programs* you wrote

- The project grade will be based on the paper, which should look like a conference paper ($\sim$8 pages, references)

Project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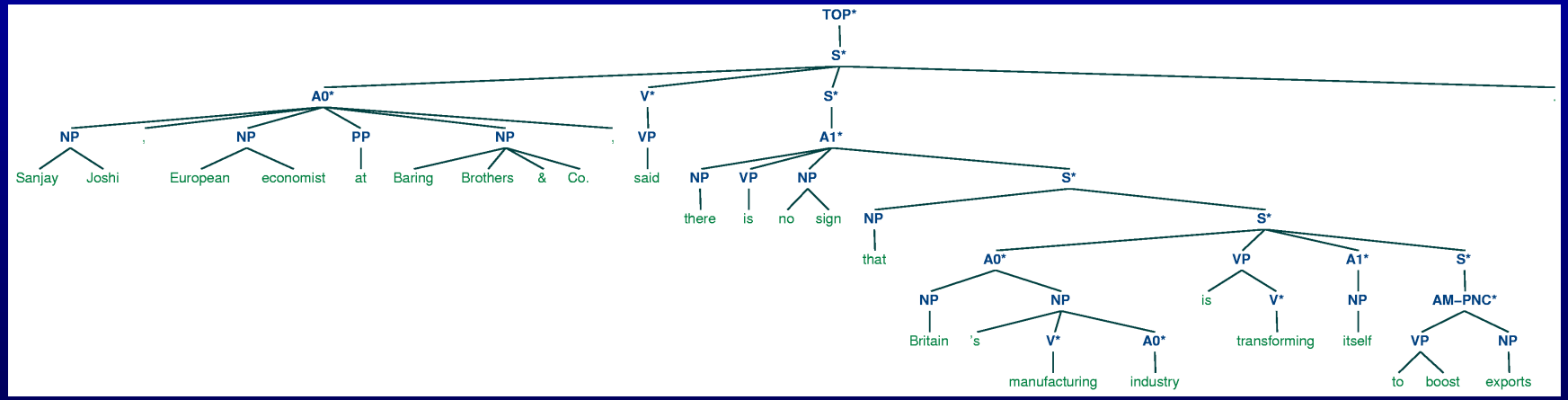
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Project

- Are chunks within the same clause part of the same argument?
- Feature vector:

```
NP,NP,Britain,NNP,’s,POS,yes.
NP,VP,industry,NN,is,VBZ,no.
```

- Use Timbl for classification
- Best result so far: 81.27% accuracy
- Largest source of error is PPs

Kernel functions

- Much of the power of SVMs comes from the use of kernel functions and derived feature spaces
- Linear kernels allow efficient processing of the very large feature vectors that come with a bag of words model
- Polynomial kernels capture dependencies between features
- Special purpose kernels reflect the structure of a particular problem
- Combinations of kernels are also kernels

String kernels

- *String subsequence kernels* represent as string as a bag of (possibly discontinuous) n grams
- The feature set is very large, but dot products can be computed efficiently
- Dynamic programming and suffix trees
- For text classification SSKs give a small improvement over n-gram kernels for small training sets

Tree kernels

- We can use similar tricks to compare trees by comparing common subtrees
- Given trees T_1 and T_2, with nodes N_1 and N_2, define:

$$I_i(n) = \begin{cases} 1 & \text{if subtree } i \text{ is rooted at } n \\ 0 & \text{otherwise} \end{cases}$$

- The kernel function is:

$$K(T_1, T_2) = h(T_1) \cdot h(T_2)$$

where

$$h_i(T_1) = \sum_{n_1 \in N_1} I_i(n_1)$$

or the number of times subtree i occurs in tree T_1.

Tree kernels

- The feature vector $h(T_1)$ will have as many dimensions as there are possible subtrees (which will be astronomical)
- But, the dot product $h(T_1) \cdot h(T_2)$ can only depend on dimensions for subtrees which occur in both T_1 and T_2
- Let $C(n_1, n_2)$ be the number of common subtrees rooted at n_1 and n_2
- The kernel function is:

$$\begin{aligned} K(T_1, T_2) &= h(T_1) \cdot h(T_2) \\ &= \sum_{n_1 \in N_1} \sum_{n_2 \in N_2} \sum_{i} I_i(n_1)\, I_i(n_2) \\ &= \sum_{n_1 \in N_1} \sum_{n_2 \in N_2} C(n_1, n_2) \end{aligned}$$

Tree kernels

- We can compute efficiently compute $C(n_1, n_2)$ by recursion
- If the rules applied at n_1 and n_2 are different, then there are no common subtrees and $C(n_1, n_2) = 0$
- If the rules are the same and n_1 and n_2 are preterminals, then $C(n_1, n_2) = 1$
- Otherwise:

$$C(n_1, n_2) = \prod_{i=1}^{nc(n_1)} (1 + C(ch(n_1, i), ch(n_2, i)))$$

- Worst case, K can be computed in $O(|N_1|\,|N_2|)$ time, but in practice $C(n_1, n_2) = 0$ for most n_1, n_2 and the computation is much cheaper

Tree kernels

- The number of common subtrees depends on the total number of subtrees
- To correct for this we can *normalize* this (or any) kernel:

$$\hat{K}(x_i, x_j) = \frac{K(x_i, x_j)}{\sqrt{K(x_i, x_i)\, K(x_j, x_j)}}$$

- Like the string kernel, we can add a decay term λ to give larger subtrees less weight:

$$C(n_1, n_2) = \prod_{i=1}^{nc(n_1)} (1 + \lambda\, C(ch(n_1, i), ch(n_2, i)))$$

Tree kernels

- Some parsing results (Collins and Duffy 2002):

	≤40 Words (2245 sentences)				
	LR	LP	CBs	0 CBs	2 CBs
CO99	88.5%	88.7%	0.92	66.7%	87.1%
VP	89.1%	89.4%	0.85	69.3%	88.2%

	≤100 Words (2416 sentences)				
	LR	LP	CBs	0 CBs	2 CBs
CO99	88.1%	88.3%	1.06	64.0%	85.1%
VP	88.6%	88.9%	0.99	66.5%	86.3%

- And named entity recognition:

	P	R	F
MaxEnt	84.4%	86.3%	85.3%
VP	86.1%	89.1%	87.6%

Kernel functions

- Implementation available at `http://www.isi.edu/~hdaume/SVMsequel/`
- Similar kernels have been proposed for dependency structures, tag sequences, etc.
- A general divide and conquer strategy for designing kernels
- *Locality-improved kernels* have been used in image processing and bioinformatics
- Specific domain knowledge may also be built into the kernel function (*codon-improved kernels* in bioinformatics)
- The benefits of kernel methods have only begun to be explored in linguistics

Support vector machines

- Support Vector Machines come from separating hyperplanes + margin error bound + kernel functions + optimization
- The math is daunting, but there are a number of SVM libraries that are reasonably efficient and easy to use
- Many, many model variants and training methods
- Generally give very high performance (as in accuracy), but don’t scale to large training sets well
- Designing appropriate kernel function for linguistic problems

Floating point arithmetic

- Digital computers can’t represent real numbers:

```
bulba% python
Python 2.2.1 (#1, Aug 30 2002, 12:15:30)
[GCC 3.2 20020822 (Red Hat Linux Rawhide 3.2-4)] on linux2
Type "help", "copyright", "credits" or "license" for more informatio
>>> 3.3
3.2999999999999998
>>>
```

- Financial calculations use integers
- Scientific calculations use approximations, which vary in their accuracy
- Standard for floating point calculations: IEEE 754

Floating point arithmetic

- Floating point numbers are stored as a *mantissa* and an *exponent*
- IEEE floating point formats:

precision	min	max	eps	digits
single	1.2×10^{-38}	3.4×10^{38}	1.2×10^{-7}	7
double	2.2×10^{-308}	1.8×10^{308}	2.2×10^{-16}	16

- Just because you can represent 10^{300} doesn't mean you get 300 significant digits!
- Default in python and perl is double precision
- Don't use single precision (`float`) unless you have a good reason

Floating point arithmetic

- It's easy to lose precision:

$$1000.2 - 1000.0 = 0.200012$$

- Things to watch out for:
  - ⋆ subtractions of numbers that are nearly equal,
  - ⋆ additions of numbers whose magnitudes are nearly equal, but whose signs are opposite
  - ⋆ additions and subtractions of numbers that differ greatly in magnitude

- Exact comparisons between floating point numbers can be misleading

- The same operations performed in a different order or on different hardware may given different results

A look back

- We’ve come a long way, from flipping coins to Support Vector Machines
- Non-parametric methods:
  - decision trees
  - instance-based learning
  - transformation-based learning
  - perceptron
  - support vector machines
- Parametric methods:
  - naive Bayes
  - maximum entropy

A look back

- One theme that runs through machine learning research is the way we characterize *generalization*
- curse of dimensionality
- bias vs. variance
- overtraining
- simplicity
- capacity

A look ahead

- Some current directions in machine learning for NLP:
  - ⋆ getting at ‘deep’ structures
  - ⋆ task-specific representations (remember, there’s no free lunch!)
  - ⋆ scaling methods to deal with huge datasets
- Data mining uses machine learning to find patterns in unstructured data collections. . .
- . . . which we’ll be looking at in more detail in the fall