Support Vector Machines and Kernel Methods for Co-Reference Resolution

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2007 Summer Workshop on Human Language Technology
Center for Language and Speech Processing
John Hopkins University
Baltimore, Agust 22, 2007

Outline

- Motivations
- Support Vector Machines
- Kernel Methods
  - Polynomial Kernel
  - Sequence Kernels
  - Tree kernels
- Kernels for Co-reference problem
  - An effective syntactic structure
  - Mention context via word sequences
- Experiments
- Conclusions

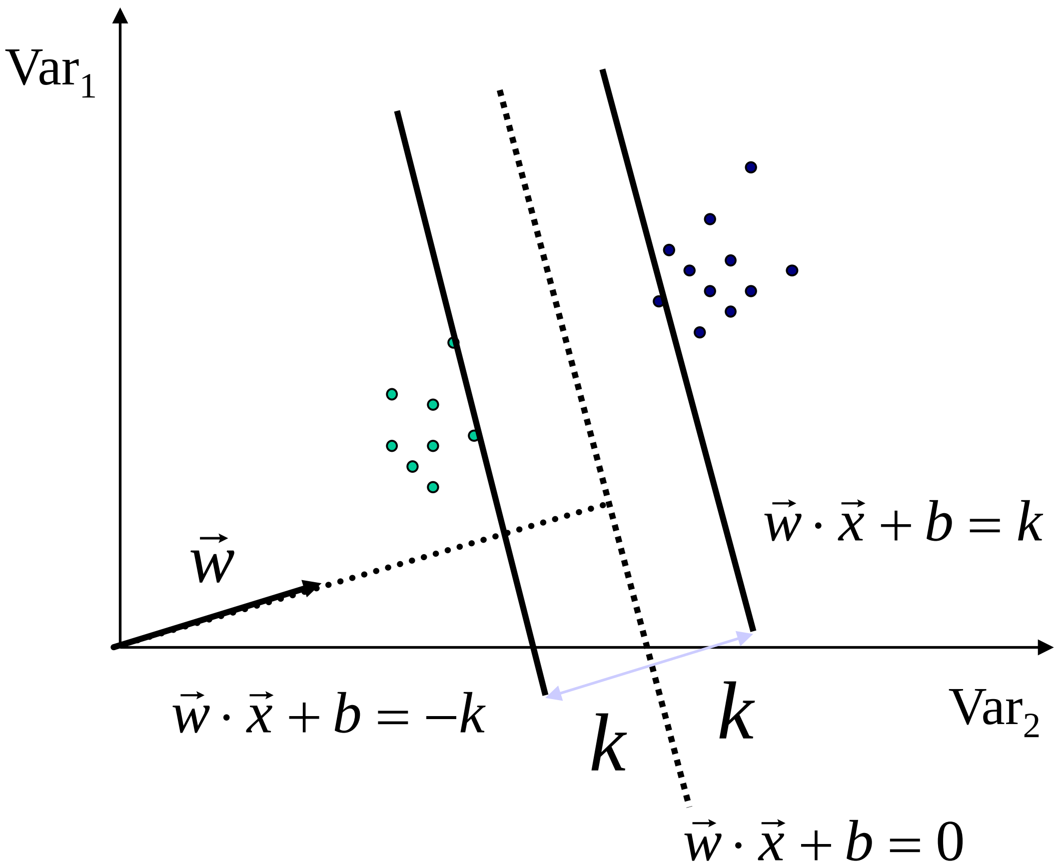
Motivations

- Intra/Cross document coreference resolution require the definition of complex features, i.e.
  - syntactic/semantic structures
- For pronoun resolution
  - Preference factors: Subject, Object, First-Mention, Definite NP
  - Constraint factors: C-commanding,…
- For non-pronoun
  - Predicative Structure, Appositive Structure

Motivations (2)

- How to represent such structures in the learning algorithm?
- How to combine different features ?
- How to select the relevant ones?
- Kernel methods allows us to
  - represent structures in terms of substructures (high dimensional feature spaces)
  - define implicit and abstract feature spaces
- Support Vector Machines “select” the relevant features
  - Automatic Feature engineering side-effect

Support Vector Machines



The margin is equal to $\dfrac{2|k|}{\|w\|}$

We need to solve

$$\max \frac{2|k|}{\|\vec{w}\|}$$

$$\vec{w} \cdot \vec{x} + b \geq +k, \text{ if } \vec{x} \text{ is positive}$$

$$\vec{w} \cdot \vec{x} + b \leq -k, \text{ if } \vec{x} \text{ is negative}$$

SVM Classification Function and the Kernel Trick

- From the primal form

$$f(\vec{x}) = \operatorname{sgn}(\vec{x} \cdot \vec{w} + b)$$

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$$\operatorname{sgn}\left(\sum_{i=1..\ell} y_i \alpha_i \phi(o_i) \cdot \phi(o) + b \right) = \operatorname{sgn}\left(\sum_{i=1..\ell} y_i \alpha_i k(o_i, o) + b \right)$$

where ℓ is the number of training examples

Flat features (Linear Kernel)

- Documents in Information Retrieval are represented as word vectors

$$\vec{x} = (0, .., 1, .., 0, .., 0, .., 1, .., 0, .., 0, .., 1, .., 0, .., 0, .., 1, .., 0, .., 1)$$

buy acquisition stocks sell market

- The dot product $\vec{x} \cdot \vec{z}$ counts the number of features in common
- This provides a sort of *similarity*

Feature Conjunction (polynomial Kernel)

- The initial vectors are mapped in a higher space

$$\Phi : \langle x_1, x_2, x_3 \rangle \rightarrow \langle x_1, x_2, x_3, x_1 x_2, x_1 x_3, x_2 x_3 \rangle$$

$$\Phi : \langle z_1, z_2, z_3 \rangle \rightarrow \langle z_1, z_2, z_3, z_1 z_2, z_1 z_3, z_2 z_3 \rangle$$

- ⟨`Stock, Market,Downtown`⟩ → ⟨`Stock, Market, Downtown, Stock+Market, Downtown+Market, Stock+Downtown`⟩

- We can efficiently compute the scalar product as

$$K_{Poly}\left(\langle x_1, x_2, x_3 \rangle, \langle z_1, z_2, z_3 \rangle\right) = \Phi\left(\langle x_1, x_2, x_3 \rangle\right) \cdot \Phi\left(\langle z_1, z_2, z_3 \rangle\right) =$$

$$= \left(\langle x_1, x_2, x_3 \rangle \cdot \langle z_1, z_2, z_3 \rangle + 1\right)^2$$

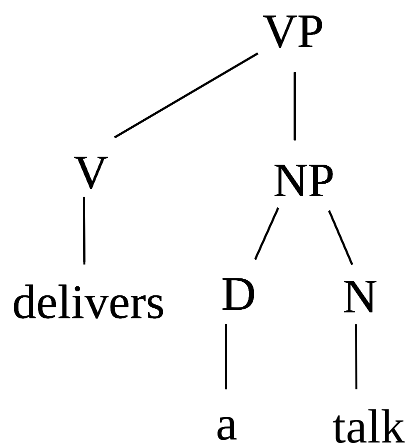
String Kernel

- Given two strings, the number of matches between their substrings is evaluated
- E.g. Bank and Rank
  - B, a, n, k, Ba, Ban, Bank, Bk, an, ank, nk,..
  - R, a , n , k, Ra, Ran, Rank, Rk, an, ank, nk,..
- String kernel over sentences and texts
- Huge space but there are efficient algorithms

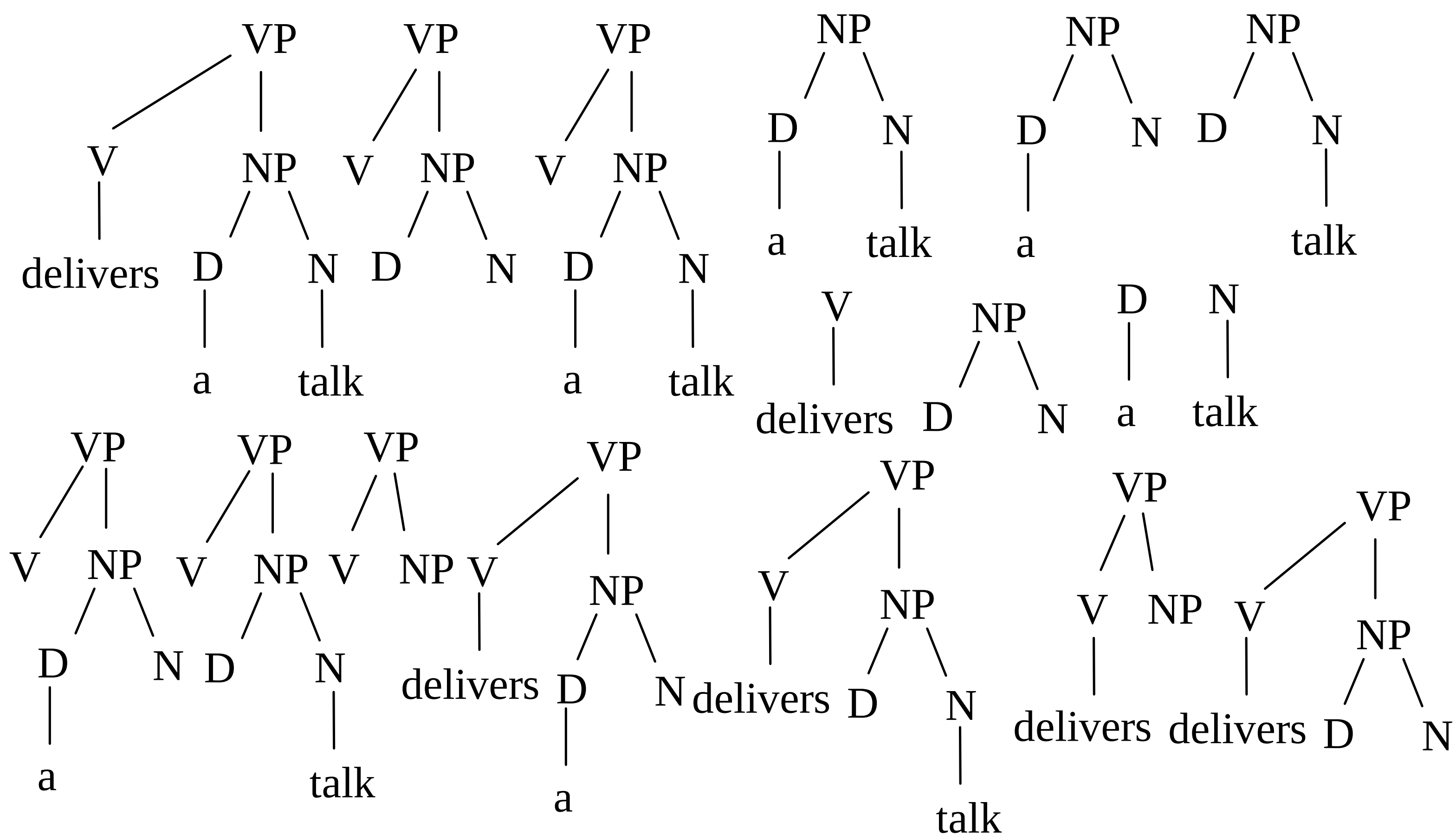
Word Sequence Kernel

- String kernels where the symbols are words
- e.g. “so **Bill Gates** says that” ⇒
  - `Bill Gates says that`
  - `Gates says that`
  - `Bill says that`
  - `so Gates says that`
  - `so says that`
  - …

A Tree Kernel
[Collins and Duffy, 2002]

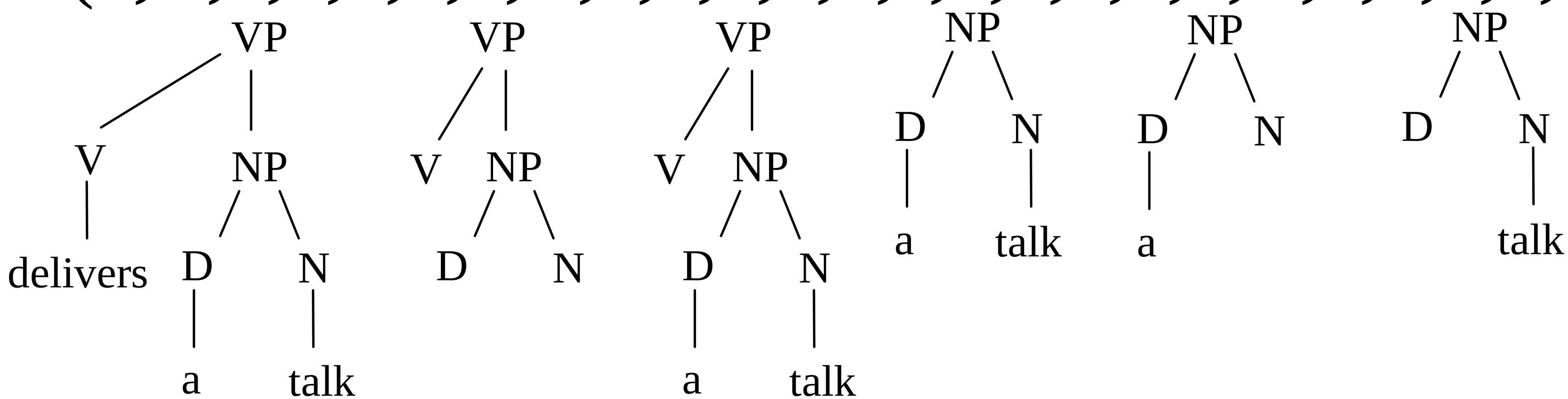


The overall SST fragment set



Explicit kernel space

$$\vec{x} = (0, ..,1,..,0,..,1, ..,0,..,1,..,0, .,1,..,0,..,1, ..,0,..,1,..,0)$$



- Given another vector $\vec{z}$,
- $\vec{x} \cdot \vec{z}$ counts the number of common substructures

Implicit Representation

$$\vec{x} \cdot \vec{z} = \phi(T_x) \cdot \phi(T_z) = K(T_x, T_z) =$$
$$= \sum_{n_x \in T_x} \sum_{n_z \in T_z} \Delta(n_x, n_z)$$

- [Collins and Duffy, ACL 2002] evaluate Δ in O(n[2]):

$$\Delta(n_x, n_z) = 0, \text{ if the productions are different else}$$
$$\Delta(n_x, n_z) = 1, \text{ if pre-terminals else}$$
$$\Delta(n_x, n_z) = \prod_{j=1}^{nc(n_x)} (1 + \Delta(ch(n_x, j), ch(n_z, j)))$$

Kernels for Co-reference problem: Syntactic Information

- Syntactic knowledge is important
  - For pronoun resolution
    - Subject, Object, First-Mention, Definite NP, C-commanding,…?
  - For non-pronoun
    - Predicative Structure, Appositive Structure …
- Source of syntactic knowledge: Parse Tree:
  - How to utilize such knowledge…

Previous Works on Syntactic knowledge

- Define a set of syntactic features extracted from parse trees
  - whether a candidate is a subject NP
  - whether a candidate is an object NP
  - whether a candidate is c-commanding the anaphor
  - ….
- Limitations
  - Manually design a set of syntactic features
  - By linguistic intuition
  - Completeness, Effectiveness?

Incorporate structured syntactic knowledge – main idea

- Use parse tree directly as a feature
- Employ a tree kernel to compare the similarity of the tree features in two instances
- Learn a SVM classifier

Syntactic Tree feature

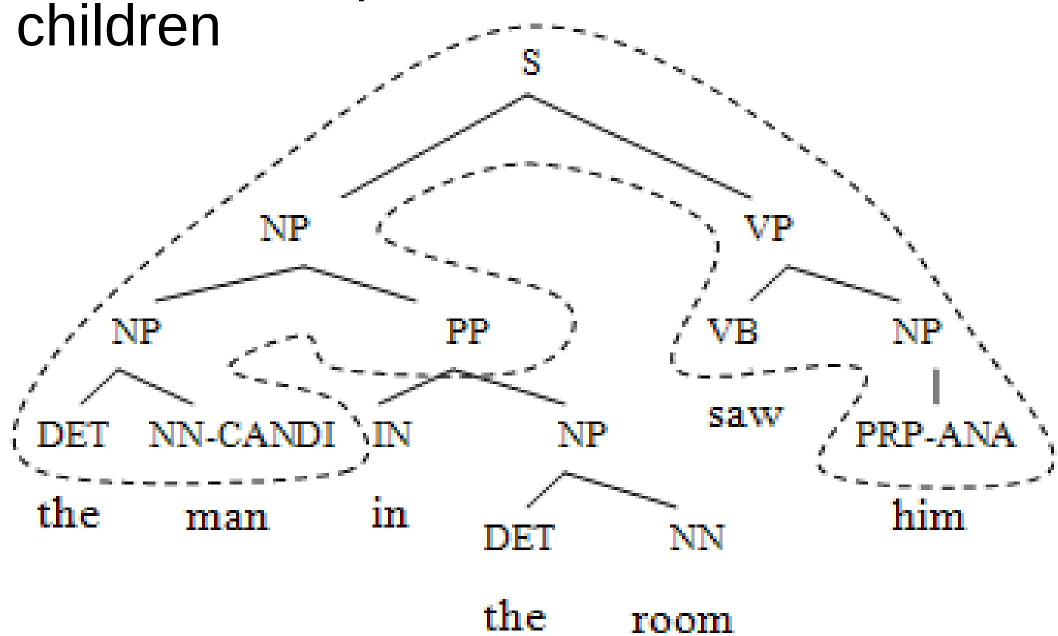
- Subtree that covers both anaphor and antecedent candidate

⇒ syntactic relations between anaphor & candidate (subject, object, c-commanding, predicate structure)

- Include the nodes in path between anaphor and candidate, as well as their first_level children

–"*the man* in the room saw *him*"

– inst("the man", "him")



Context Sequence Feature

- A word sequence representing the mention expression and its context
  - Create a sequence for a mention

–“Even so, **Bill Gates** says that he just doesn’t understand our infatuation with thin client versions of Word ”

– (so)(,) (**Bill**)(**Gates**)(says)(that)

Composite Kernel

- different kernels for different features
  - Poly Kernel: for baseline flat features
  - Tree Kernel : for syntax trees
  - Sequence Kernel: for word sequences
- A composite kernel for all kinds of features
- Composite Kernel =

  TreeK*PolyK+PolyK+SeqenceK

Results for pronoun resolution

	MUC-6			ACE-02-BNews		
	R	P	F	R	P	F
All attribute value features	64.3	63.1	63.7	58.9	68.1	63.1
+Syntactic Tree + Word Sequence	65.2	80.1	**71.9**	65.6	69.7	**67.6**

Results for over-all coreference Resolution using SVMs

	MUC-6			ACE02-BNews		
	R	P	F	R	P	F
BaseFeature SVMs	61.5	67.2	64.2	54.8	66.1	59.9
BaseFeature + Syntax Tree	63.4	67.5	65.4	56.6	66.0	60.9
BaseFeature+SyntaxTree + Word Sequences	64.4	67.8	66.0	57.1	65.4	61.0
All Sources of Knowledge	60.1	76.2	67.2	60.0	65.4	63.0

Conclusions

- SVMs and Kernel methods are powerful tools to design intra/cross doc coreference systems
- SVMs allows for
  - better exploit attribute/vector features
  - the use of syntactic structures
  - the use of word sequence context
- The results show noticeable improvement over the baseline

Thank you