

# Coreference Resolution

Rule-based approaches

# Rule-based

- Before machine learning methods were used, rule-based methods were the go-to methods in coreference resolution
- Until 2011, these were even state-of-the-art (Stanford sieve)

- E.g. CoNLL:

Track	Mentions	MUC			$B^3$			durchschn. F1
		P	R	F1	P	R	F1	
Geschlossen	Nicht Gold	57.5	61.8	59.6	68.2	68.4	68.3	57.8
Offen	Nicht Gold	59.3	62.8	61.0	69.0	68.9	68.9	58.3
Geschlossen	Gold	62.1	65.9	63.9	70.6	69.5	70.0	60.7
Offen	Gold	63.9	66.9	65.4	71.5	70.1	70.8	61.4

- There as the best system!

# Rule-based

- Main idea:
  - Resolve the mentions in the order they are found in the text
  - For each Mention:
    - Find a candidate set ("aggregate")
    - Filter the candidates by hard constraints ("filter")
    - And sort the candidates by soft constraints ("rank")
  - Main idea of the improvements of the system from Stanford:  
Resolve mentions by their security on "Easy-First" to minimize consequential errors!

# Rule-based - Constraints

- Hard constraints
  - Morphological constraints (gender, numerus)
  - Syntactic constraints (binding theory: "he combs his ..." vs "he combs himself")
  - Semantic constraints ("buildings cannot walk")
- Soft constraints ("preferences")
  - Syntactic ("resolving to subjects is better than resolving to objects")
  - Semantic ("Older people draw pensions more often than younger people")
  - Morphological (German example: "A neuter can be resolved to masculine antecedents as well as feminine antecedents")
    - Example with the German diminutive form
      - „Das Bürschchen“ (the little boy) → antecedent masculine
      - „Das Mädchen“ (the little girl) → antecedent feminine

# Lappin and Leass 1994

- Idea: Maintain a discourse model, in which there are representations for potential referents.
- Lappin and Leass 1994 propose a discourse model in which potential referents have degrees of salience.
- They try to resolve (**pronoun**) references by finding highly salient referents compatible with pronoun agreement features.
- In effect, they incorporate:
  - recency
  - syntax-based preferences
  - agreement, but no (other) semantics

# Lappin and Leass 1994

- First, we assign a number of salience factors & salience values to each referring expression.
- The salience values (weights) are derived by experimentation on a certain corpus.

# Lappin and Leass 1994

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	80
Existential emphasis	70
Accusative emphasis	50
Indirect object emphasis	40
Non-adverbial emphasis	50
Head noun emphasis	80

# Lappin and Leass 1994

- Non-adverbial emphasis is to penalize “demarcated adverbial PPs” (e.g., “In his hand, ...”) by giving points to all other types.
- Head noun emphasis is to penalize embedded referents.
- Other factors & values:
  - Grammatical role parallelism: 35
  - Cataphora: -175



# Lappin and Leass 1994

- The algorithm employs a simple weighting scheme that integrates the effects of several preferences:
  - For each new entity, a representation for it is added to the discourse model and salience value computed for it.
  - Salience value is computed as the sum of the weights assigned by a set of salience factors.
    - The weight a salience factor assigns to a referent is the highest one the factor assigns to the referent's referring expression.
  - Salience values are cut in half each time a new sentence is processed.

# Lappin and Leass 1994

- The steps taken to resolve a **pronoun** are as follows:
  - Collect potential referents (four sentences back); (“**aggregate**”)
  - Remove potential referents that don’t semantically agree;
  - Remove potential referents that don’t syntactically agree; (“**filter**”)
  - Compute salience values for the rest of potential referents;
  - Select the referent with the highest salience value. (“**rank**”)

# Lappin and Leass 1994

- Salience factors apply per NP, i.e., referring expression
- However, we want the salience for a potential referent
  - So, all NPs determined to have the same referent are examined
- The referent is given the sum of the highest salience factor associated with any such referring expression
- Salience factors are considered to have scope over a sentence
  - So references to the same entity over multiple sentences add up
  - While multiple references within the same sentence don't

# Example

- John saw a beautiful Acura Integra at the dealership.
- He showed it to Bob.
- He bought it.

# Example

- John saw a beautiful Acura Integra at the dealership.

Referent	Phrases	Value
John	{John}	?
Integra	{a beautiful Acura Integra}	?
dealership	{the dealership}	?

# John

John saw a beautiful Acura Integra at the dealership.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	80
Existential emphasis	
Accusative emphasis	
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80

# Integra

John saw a beautiful Acura Integra at the dealership.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	
Existential emphasis	
Accusative emphasis	50
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80

# dealership

John saw a beautiful Acura Integra at the dealership.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	
Existential emphasis	
Accusative emphasis	
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80



# Example

- John saw a beautiful Acura Integra at the dealership.

Referent	Phrases	Value
John	{John}	310
Integra	{a beautiful Acura Integra}	280
dealership	{the dealership}	230

# Example

- He showed it to Bob.

Referent	Phrases	Value
John	{John}	310/2
Integra	{a beautiful Acura Integra}	280/2
dealership	{the dealership}	230/2

Referent	Phrases	Value
John	{John}	155
Integra	{a beautiful Acura Integra}	140
dealership	{the dealership}	115

# He

He showed it to Bob.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	80
Existential emphasis	
Accusative emphasis	
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80

# Example

- He showed it to Bob.
- Gender constraint:  
“Integra” and “dealership” can’t be “he”

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	465
Integra	{a beautiful Acura Integra}	140
dealership	{the dealership}	115

It

He showed it to Bob.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	
Existential emphasis	
Accusative emphasis	50
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80

# Example

- He showed it to Bob.

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	465
Integra	{a beautiful Acura Integra}	140
dealership	{the dealership}	115

- Gender constraint: "John" can't be "it"
- Since "Integra" is more salient than "dealership" (140 > 115):  
→ "it" refers to "Integra"

# Example

- He showed it to Bob.

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	465
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	420
dealership	{the dealership}	115

# Bob

He showed it to Bob.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	
Existential emphasis	
Accusative emphasis	
Indirect object emphasis	40
Non-adverbial emphasis	50
Head noun emphasis	80



# Example

- He showed it to Bob.

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	465
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	420
Bob	{Bob}	270
dealership	{the dealership}	115

# Example

- He bought it.

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	465/2
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	420/2
Bob	{Bob}	270/2
dealership	{the dealership}	115/2

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	232.5
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	210
Bob	{Bob}	135
dealership	{the dealership}	57.5

# He

He bought it.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	80
Existential emphasis	
Accusative emphasis	
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80

# Example

- He bought it.

Referent	Phrases	Value
John	{John, he <sub>1</sub> }	232.5
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	210
Bob	{Bob}	135
dealership	{the dealership}	57.5

Since "John" is more salient than "Bob" ( $232.5 > 135$ ):  
 → "He" refers to "John"

# Example

- He bought it.

Referent	Phrases	Value
John	{John, he <sub>1</sub> , He}	542.5
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	210
Bob	{Bob}	135
dealership	{the dealership}	57.5

It

He bought it.

<b>Salience Factor</b>	<b>Salience Value</b>
Sentence recency	100
Subject emphasis	
Existential emphasis	
Accusative emphasis	50
Indirect object emphasis	
Non-adverbial emphasis	50
Head noun emphasis	80

# Example

- He bought it.

Referent	Phrases	Value
John	{John, he <sub>1</sub> , he <sub>2</sub> }	542.5
Integra	{a beautiful Acura Integra, it <sub>1</sub> }	210
Bob	{Bob}	135
dealership	{the dealership}	57.5

- Gender constraint: "John" and "Bob" can't be "it"
- Since "Integra" is more salient than "dealership" (210 > 57.5):  
→ "it" refers to "Integra"

# Example

- He bought it.

Referent	Phrases	Value
John	{John, he <sub>1</sub> , he <sub>2</sub> }	542.5
Integra	{a beautiful Acura Integra, it <sub>1</sub> , it <sub>2</sub> }	490
Bob	{Bob}	135
dealership	{the dealership}	57.5

We should have added 35 for grammatical role parallelism, but we ignore this.



# Evaluation of Lappin and Leass 1994

- Weights were arrived at by experimentation on a corpus of computer training manuals
- Combined with other filters, algorithm achieve 86% accuracy (74% / 89% inter- / intra-sentential):
  - applied to unseen data of same genre

# Current state of the art

- Coreference resolution remains an unsolved problem:
- On CoNLL: (as of December 2017 Lee: "End-to-End Neural Coreference Resolution").

	MUC			B <sup>3</sup>			CEAF <sub><math>\phi_4</math></sub>			Avg. F1
	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.	F1	
Our model (ensemble)	<b>81.2</b>	<b>73.6</b>	<b>77.2</b>	<b>72.3</b>	<b>61.7</b>	<b>66.6</b>	<b>65.2</b>	<b>60.2</b>	<b>62.6</b>	<b>68.8</b>
Our model (single)	78.4	73.4	75.8	68.6	61.8	65.0	62.7	59.0	60.8	67.2
Clark and Manning (2016a)	79.2	70.4	74.6	69.9	58.0	63.4	63.5	55.5	59.2	65.7
Clark and Manning (2016b)	79.9	69.3	74.2	71.0	56.5	63.0	63.8	54.3	58.7	65.3
Wiseman et al. (2016)	77.5	69.8	73.4	66.8	57.0	61.5	62.1	53.9	57.7	64.2
Wiseman et al. (2015)	76.2	69.3	72.6	66.2	55.8	60.5	59.4	54.9	57.1	63.4
Clark and Manning (2015)	76.1	69.4	72.6	65.6	56.0	60.4	59.4	53.0	56.0	63.0
Martschat and Strube (2015)	76.7	68.1	72.2	66.1	54.2	59.6	59.5	52.3	55.7	62.5
Durrett and Klein (2014)	72.6	69.9	71.2	61.2	56.4	58.7	56.2	54.2	55.2	61.7
Björkelund and Kuhn (2014)	74.3	67.5	70.7	62.7	55.0	58.6	59.4	52.3	55.6	61.6
Durrett and Klein (2013)	72.9	65.9	69.2	63.6	52.5	57.5	54.3	54.4	54.3	60.3