Graph-Cut-Based Anaphoricity Determination for Coreference Resolution

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Noun Phrase Coreference

Identify the noun phrases (NPs) that refer to the same entity

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  - train a coreference model, $\mathbf{P_C}$, to determine the probability that two NPs are coreferent
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How to determine whether an NP has an antecedent?

Any NP that is part of a coref chain but is not the head of the chain has an antecedent. It's an anaphoric NP.

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King George VI, into a viable monarch.

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Anaphoricity Determination

- determines whether an NP is anaphoric or not
- helps improve the precision of a coreference system

Goal

Improve learning-based coreference systems using automatically acquired anaphoricity information, by proposing a new approach to anaphoricity determination

Plan for the Talk

- Existing methods for computing and using anaphoricity info
- Our graph-cut-based approach to anaphoricity determination
- Evaluation

Methods for Computing and Using Anaphoricity Information

- Five existing methods
  - Ng & Cardie (2002)
  - Ng (2004)
  - Luo (2007)
  - Denis & Baldridge (2007)
  - Kleener (2007), Finkel & Manning (2008)

What do the methods have in common?

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- Training data creation
  - texts annotated with coreference information
  - one instance for each NP
    - positive if the NP is part of a coref chain but not head of chain
    - negative otherwise

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- They differ in terms of
  - whether they improve the output of $\mathbf{P_A}$
    - if so, how?
  - how anaphoricity info is used by the coreference system
    - as hard constraints or as soft constraints?

Ng & Cardie (2002)

Improve P_A's output?	Used as hard constraint?
✗	✓

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NP$_j$ is classified
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- Problem
  - many anaphoric NPs are misclassified (as non-anaphoric)
    - $\mathbf{P_A}$ is overly conservative in classifying an NP as anaphoric

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- decreasing ***t*** ⇒ more NPs will be classified as anaphoric
- increasing ***t*** ⇒ fewer NPs will be classified as anaphoric
- ***t*** is the "conservativeness" parameter

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- decreasing ***t*** ⇒ more NPs will be classified as anaphoric
- increasing ***t*** ⇒ fewer NPs will be classified as anaphoric
- select ***t*** to use held-out data to maximize coreference performance (i.e., F-measure)

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    - by multiplying the probabilities provided by **P_A** and **P_C**
  - find highest-scored NP partition
    - by performing a beam search through the Bell tree

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- use Integer Linear Programming (ILP) to perform joint inference for anaphoricity determination and coreference

ILP: A Motivating Example

- 3 NPs: 1, 2, 3
- $\mathbf{P_c}(1, 2) = 0.6$, $\mathbf{P_c}(1, 3) = 0.2$, $\mathbf{P_c}(2, 3) = 0.9$

  $\mathbf{P_A}(1) = 0.1$, $\mathbf{P_A}(2) = 0.9$, $\mathbf{P_A}(3) = 0.2$

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- $\mathbf{P_A}$ and $\mathbf{P_C}$'s outputs don't seem to be consistent. Why???
  - Because they are trained independently of each other
- Certain hard constraints need to be enforced
  - If $\mathbf{P_C}$ determines that NP_j is not coreferent with any NP, then $\mathbf{P_A}$ should determine that NP_j is non-anaphoric
  - **…**

ILP for Anaphoricity and Coreference

- Goal
  - jointly determine anaphoricity and coreference decisions such that all the desired constraints are satisfied

- improve anaphoricity decisions with automatically computed coreference information and manually-specified constraints

Kleener (2007), Finkel & Manning (2008)

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- Also employ ILP, but additionally impose the transitivity constraint on the coreference decisions
  - A, B are coref **and** B,C are coref   A,C are coreferent

Summary of the Five Methods

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Summary of the Five

Can we have a method that optimizes F-measure and exploits $\mathbf{P_C}$?

	Impr[illegible] $_A$ [illegible] output?	[illegible] constraint?
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exploit probabilities provided by $\mathbf{P_C}$

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Cut-Based Anaphoricity Determination

- Motivated by our desire to have a method that can
  - optimize the desired coreference evaluation metric
  - exploit probabilities provided by $\mathbf{P_C}$

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    - captures the affinity of x_i to S and T, respectively
    - large $mem_S(x_i)$ x_i is likely to be in S
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- Goal:

Maximize $$\sum_{x_i \in S, x_j \in T} sim(x_i, x_j) + \sum_{x \in S} mem_S(x) + \sum_{x \in T} mem_T(x)$$

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Put similar objects into the same set

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  - S (x_i, x_j)
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Put similar objects into the same set

Put an object to the set where its membership score is high

- Goal:

Maximize $$\sum_{x_i \in S, x_j \in T} sim(x_i, x_j) + \sum_{x \in S} mem_S(x) + \sum_{x \in T} mem_T(x)$$

Solving this Problem Using MinCut

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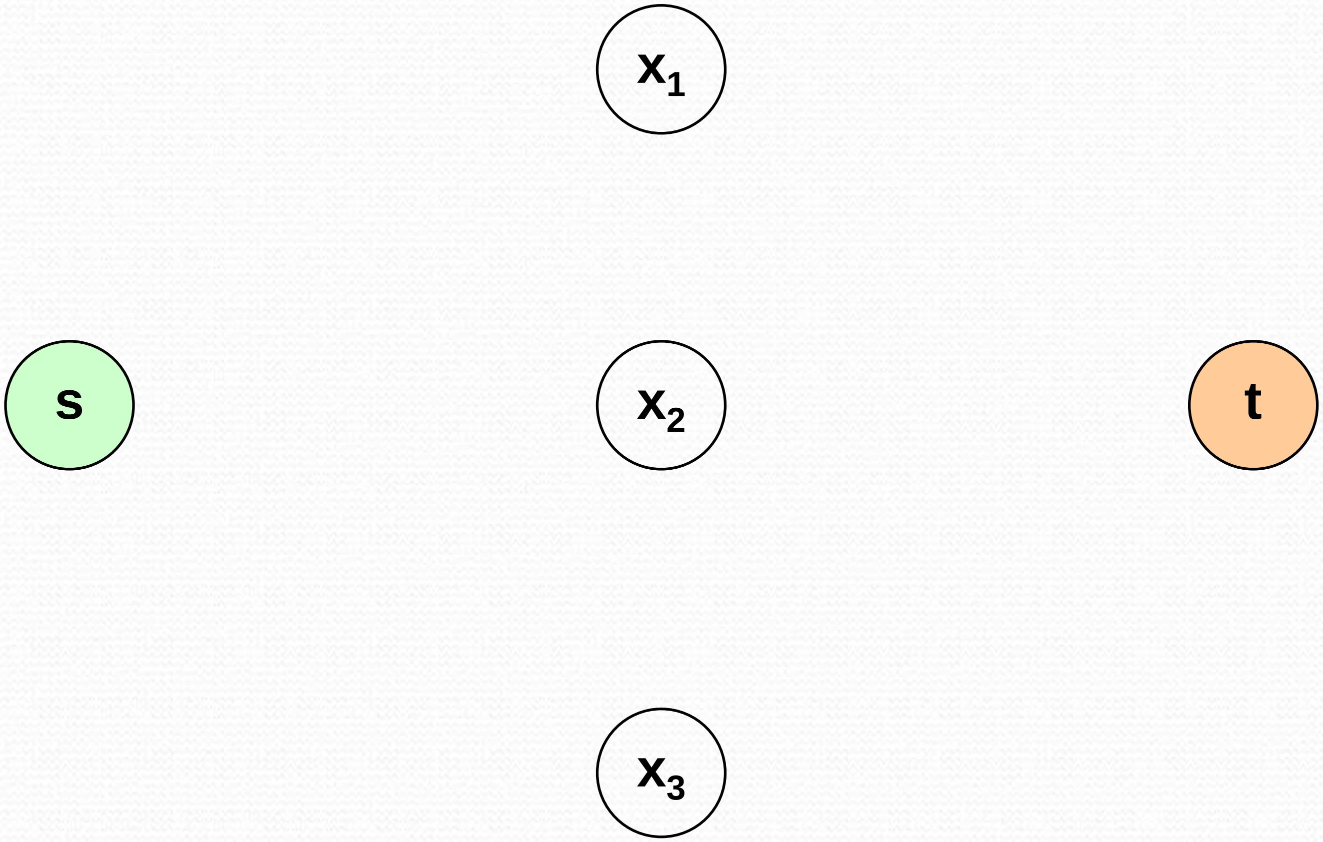

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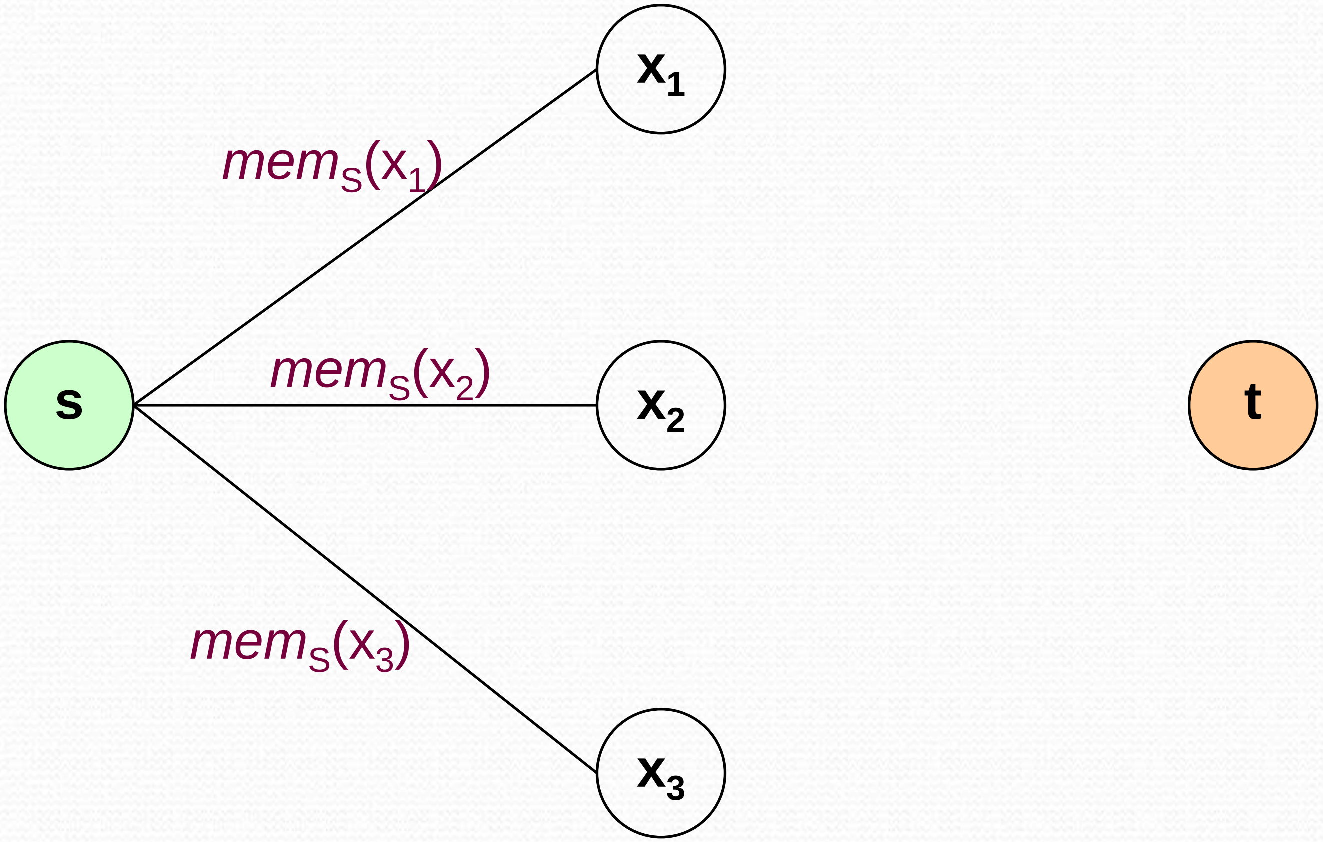

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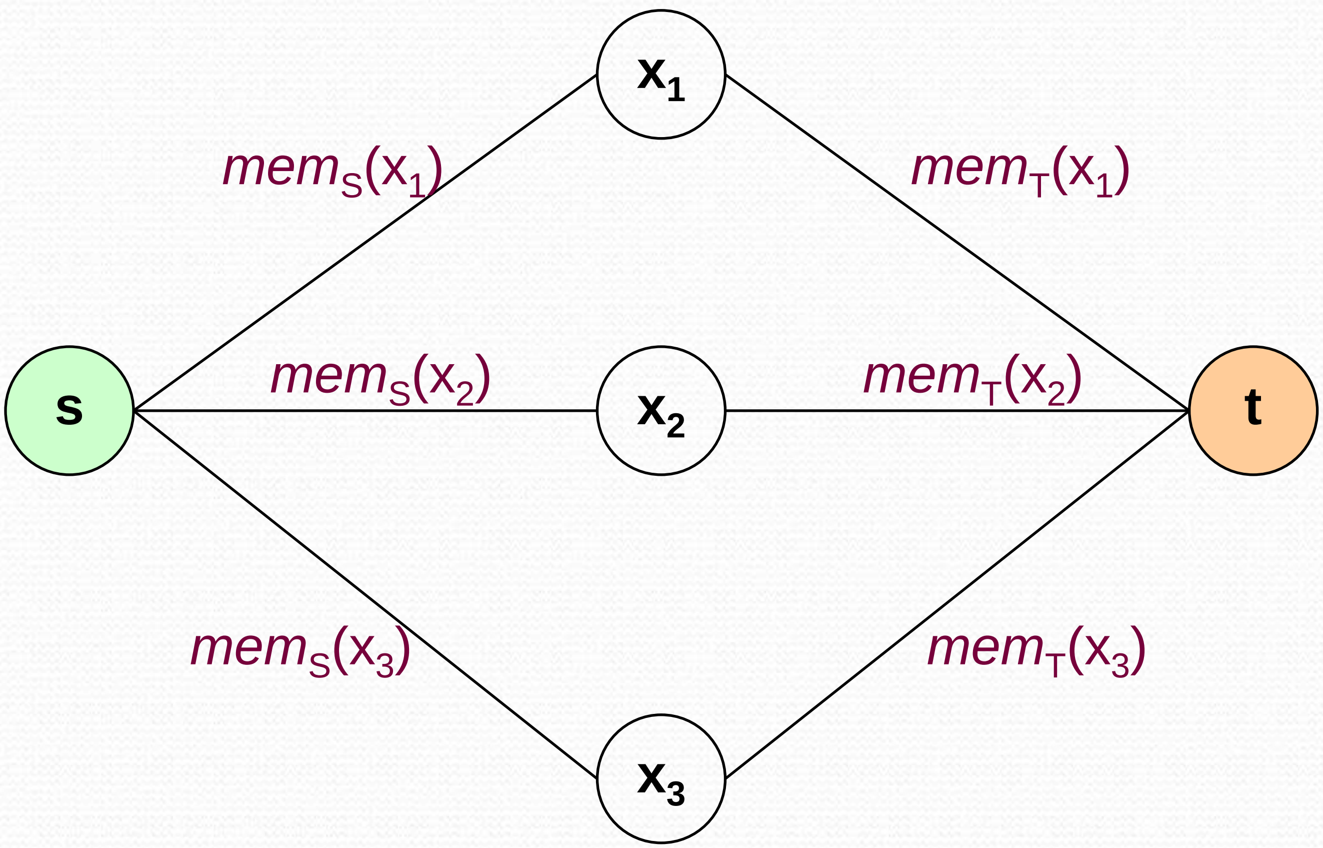

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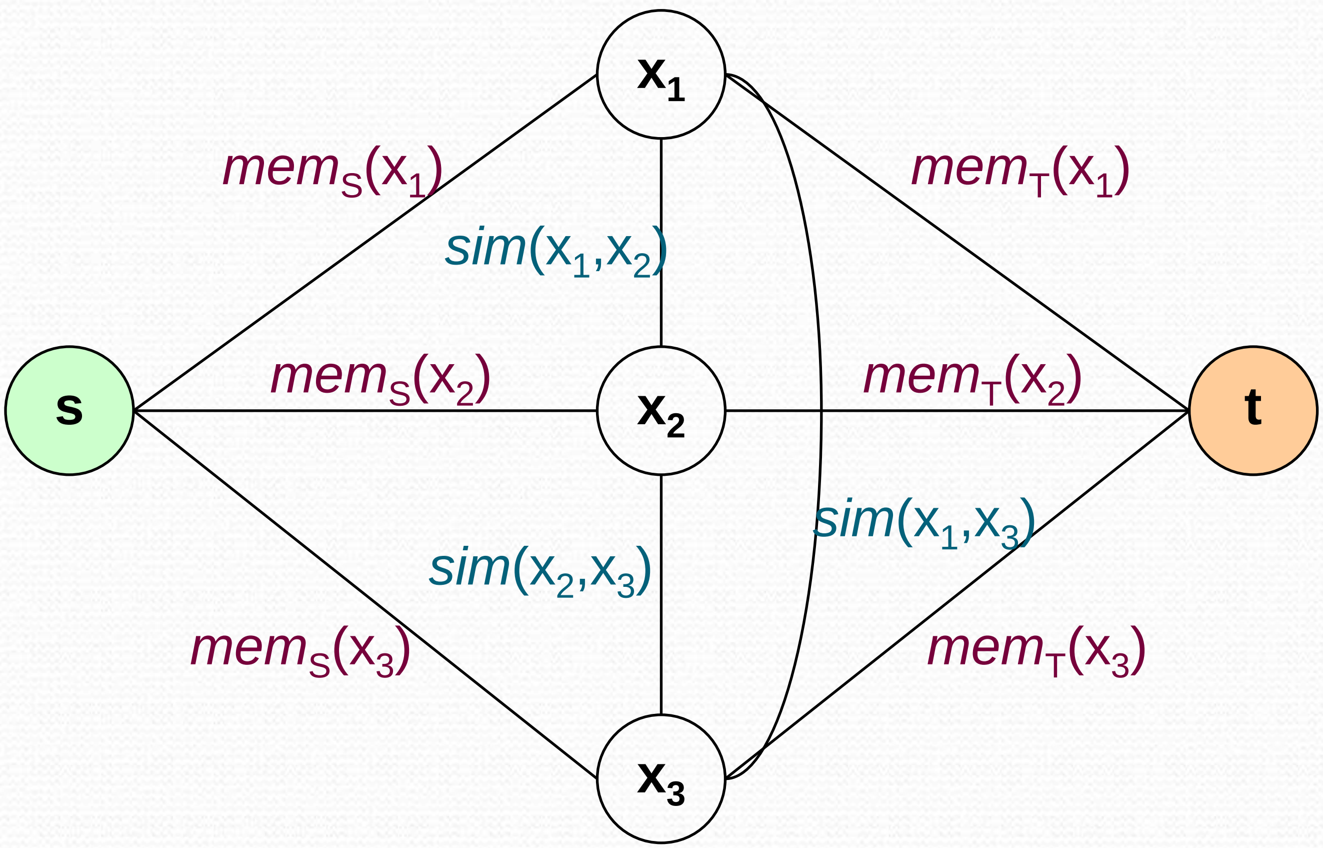

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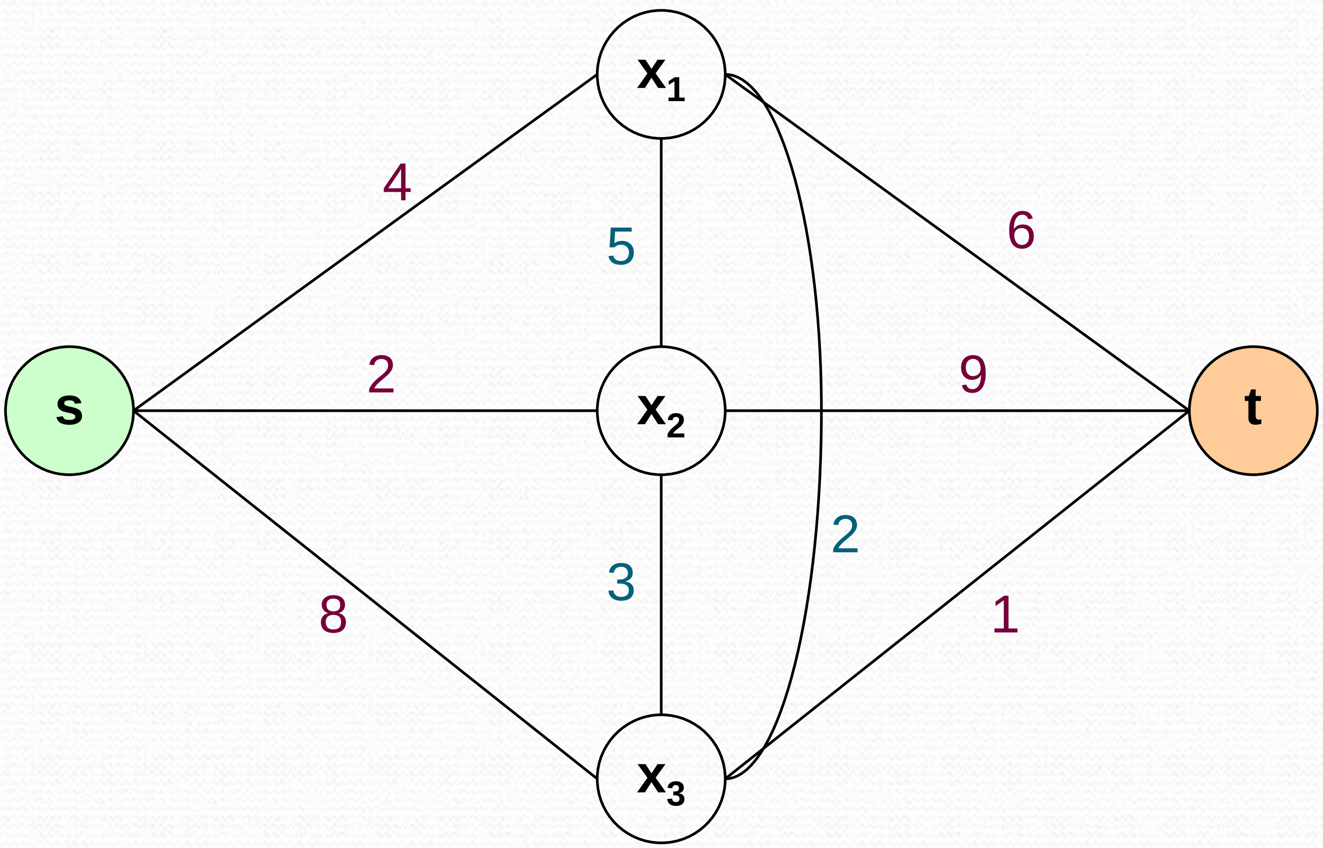

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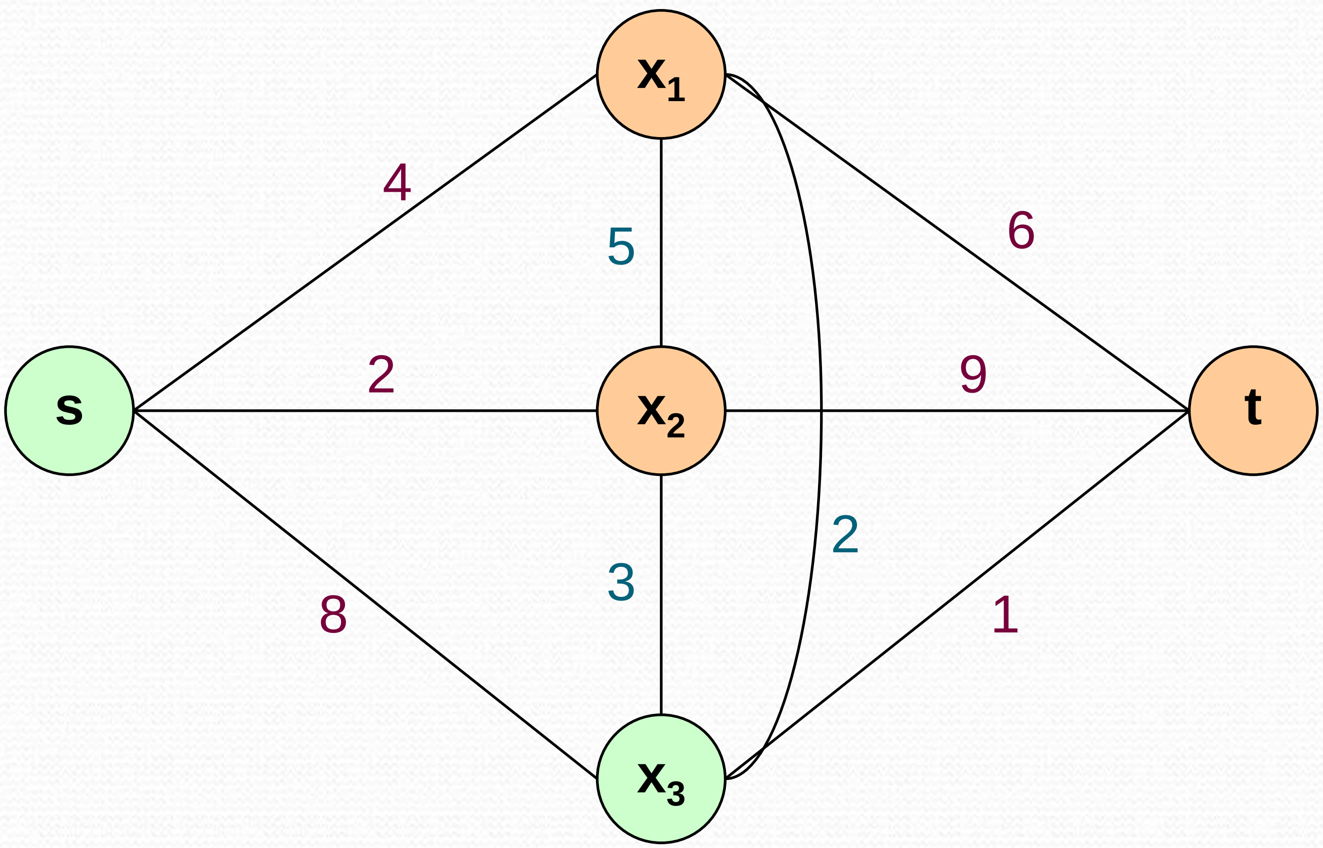

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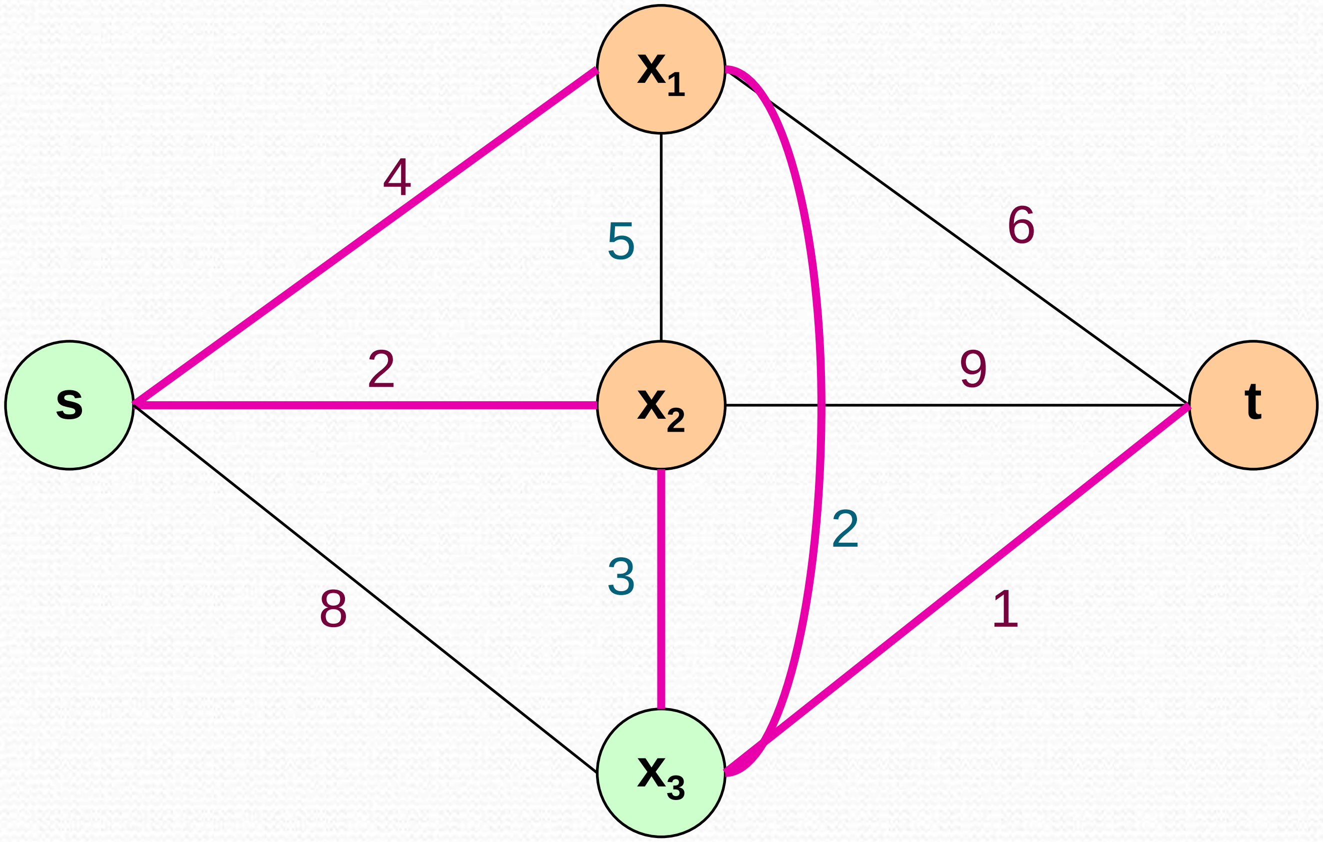

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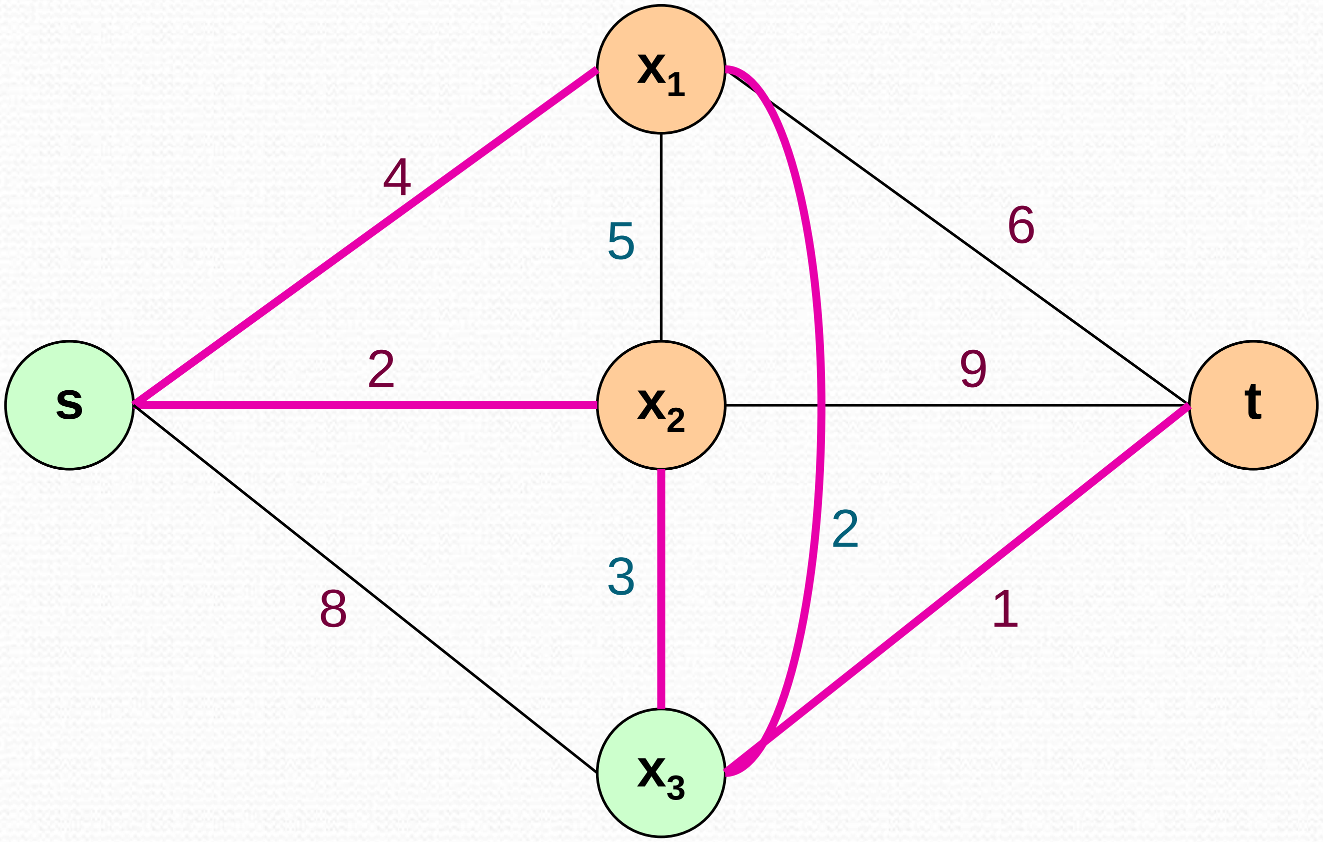
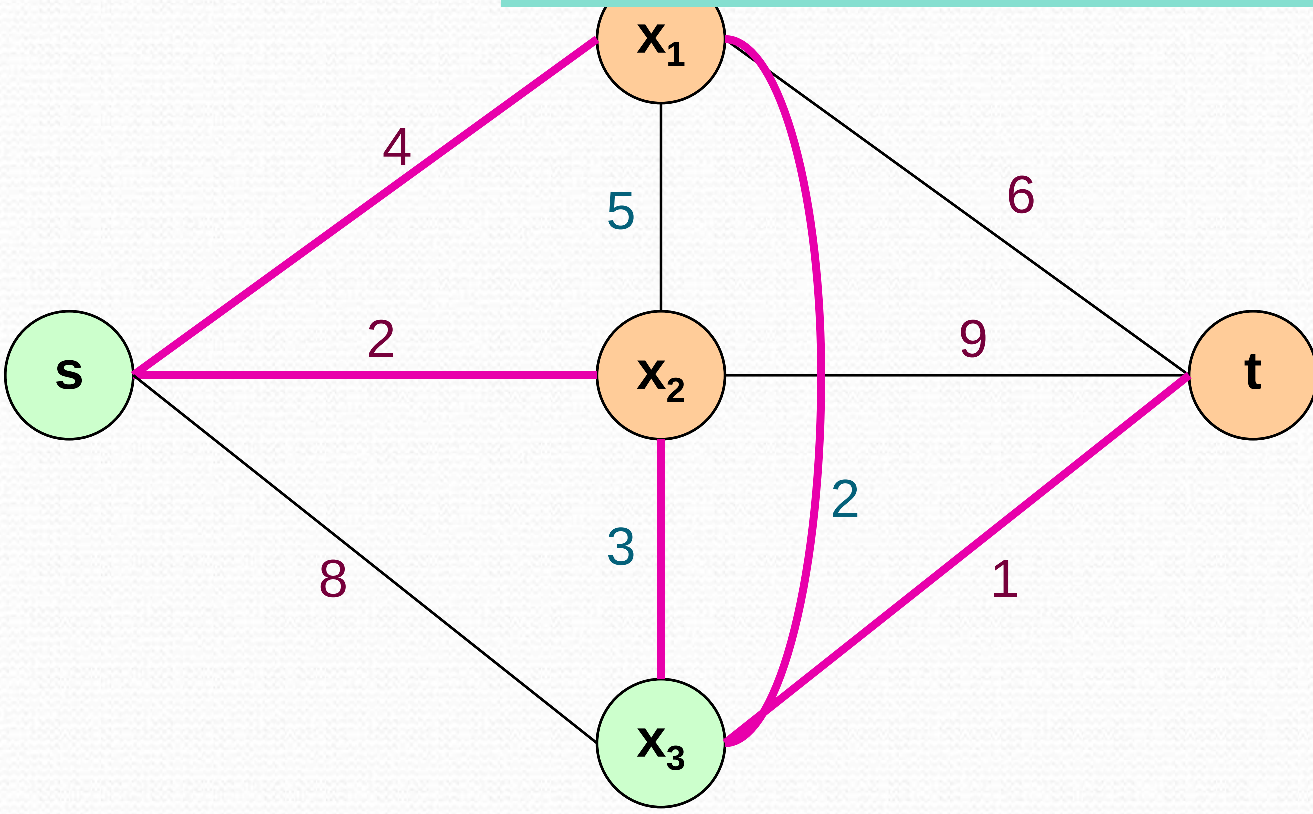


- Efficient algorithms for finding the mincut exist

Solving this Problem Using MinCut

How to recast anaphoricity determination as a graph mincut problem?



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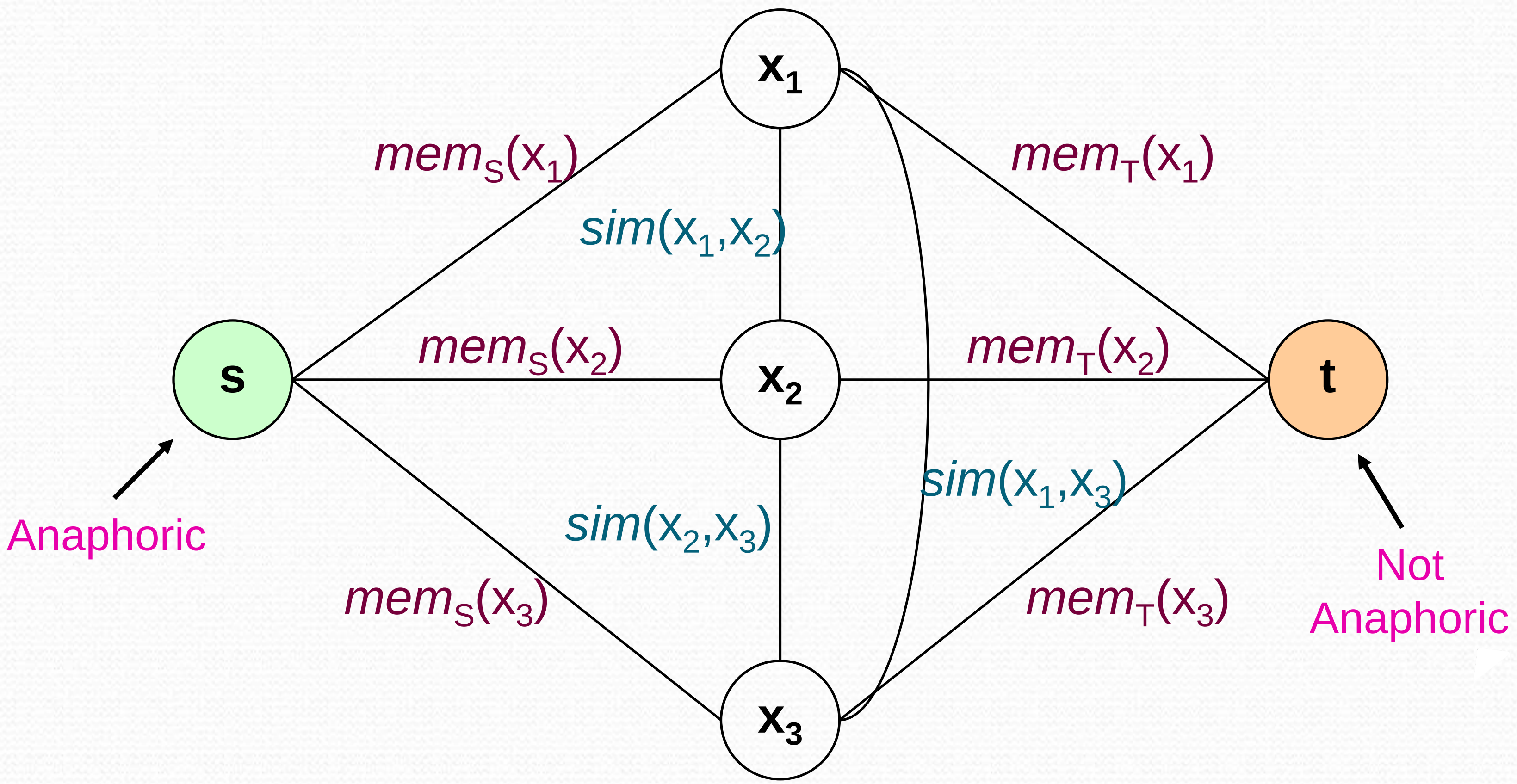
Cut-Based Anaphoricity Determination



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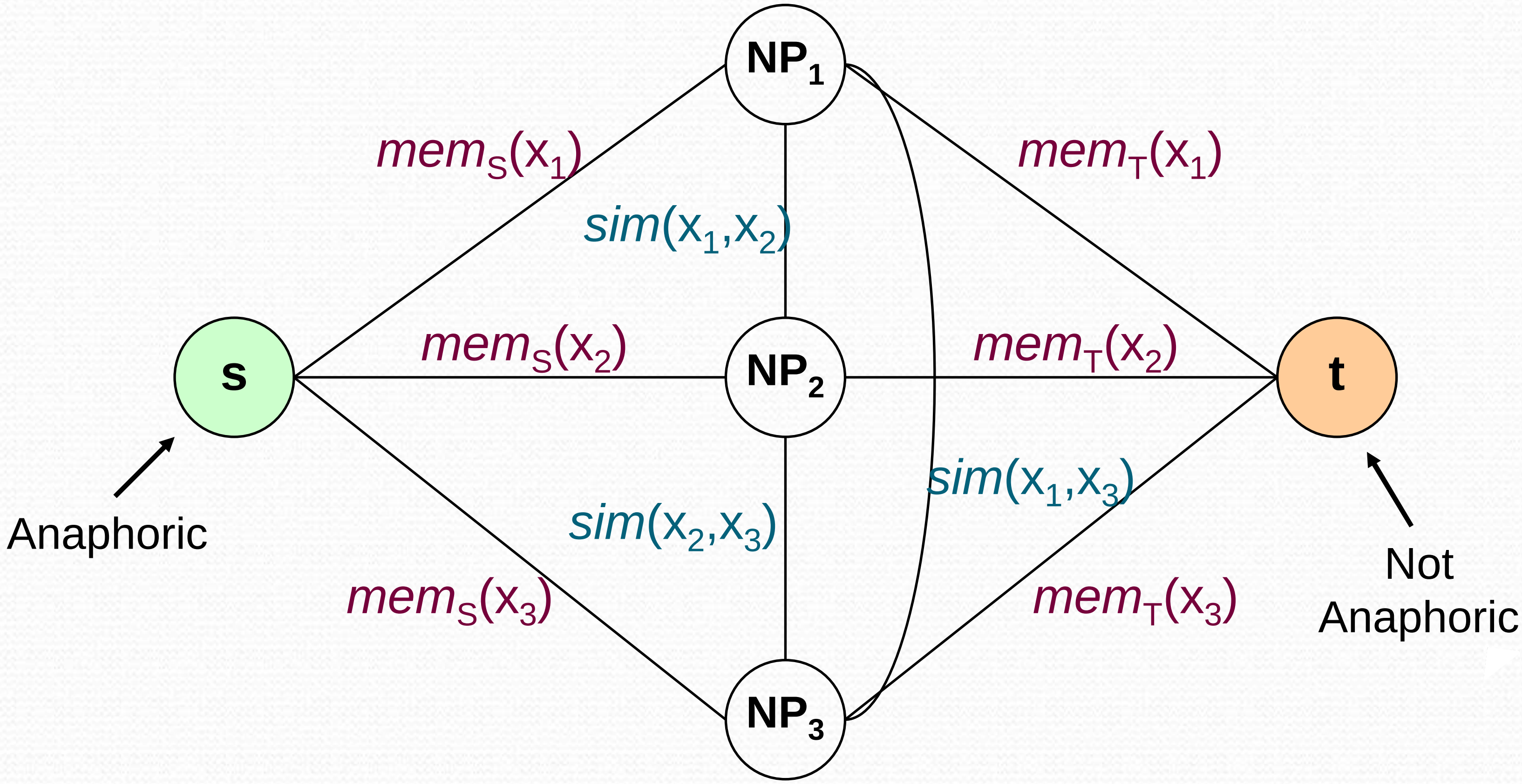

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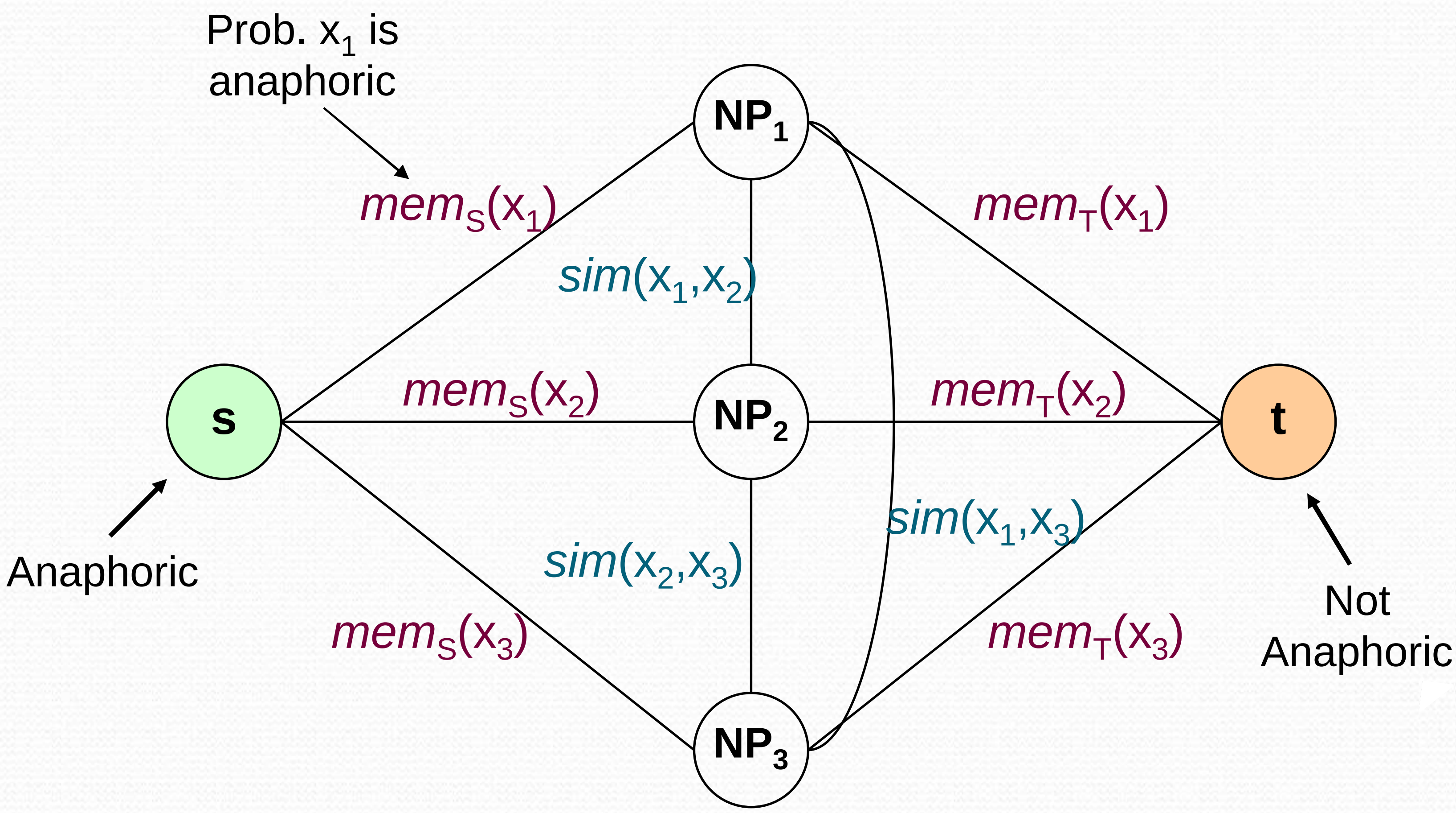

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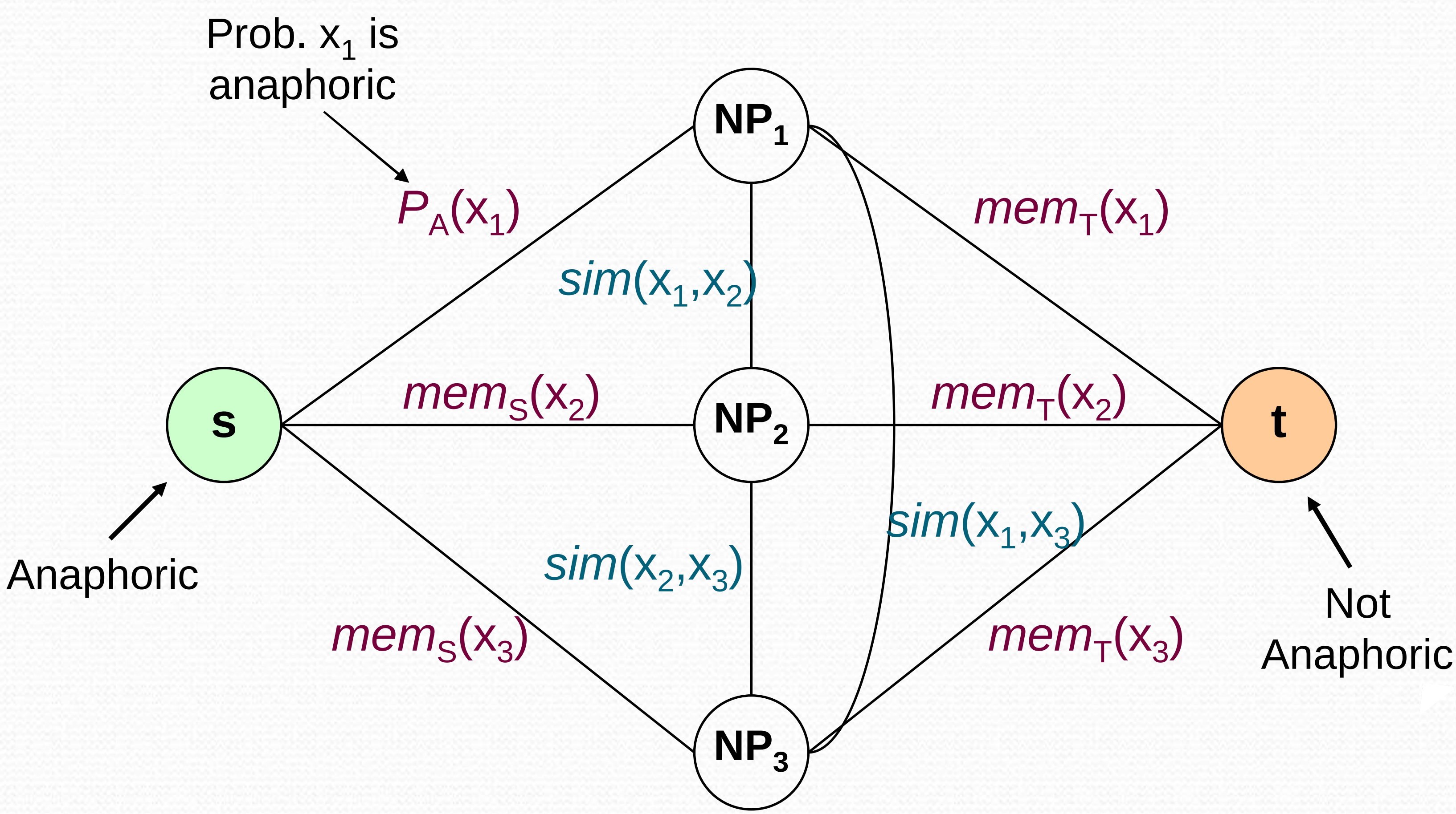

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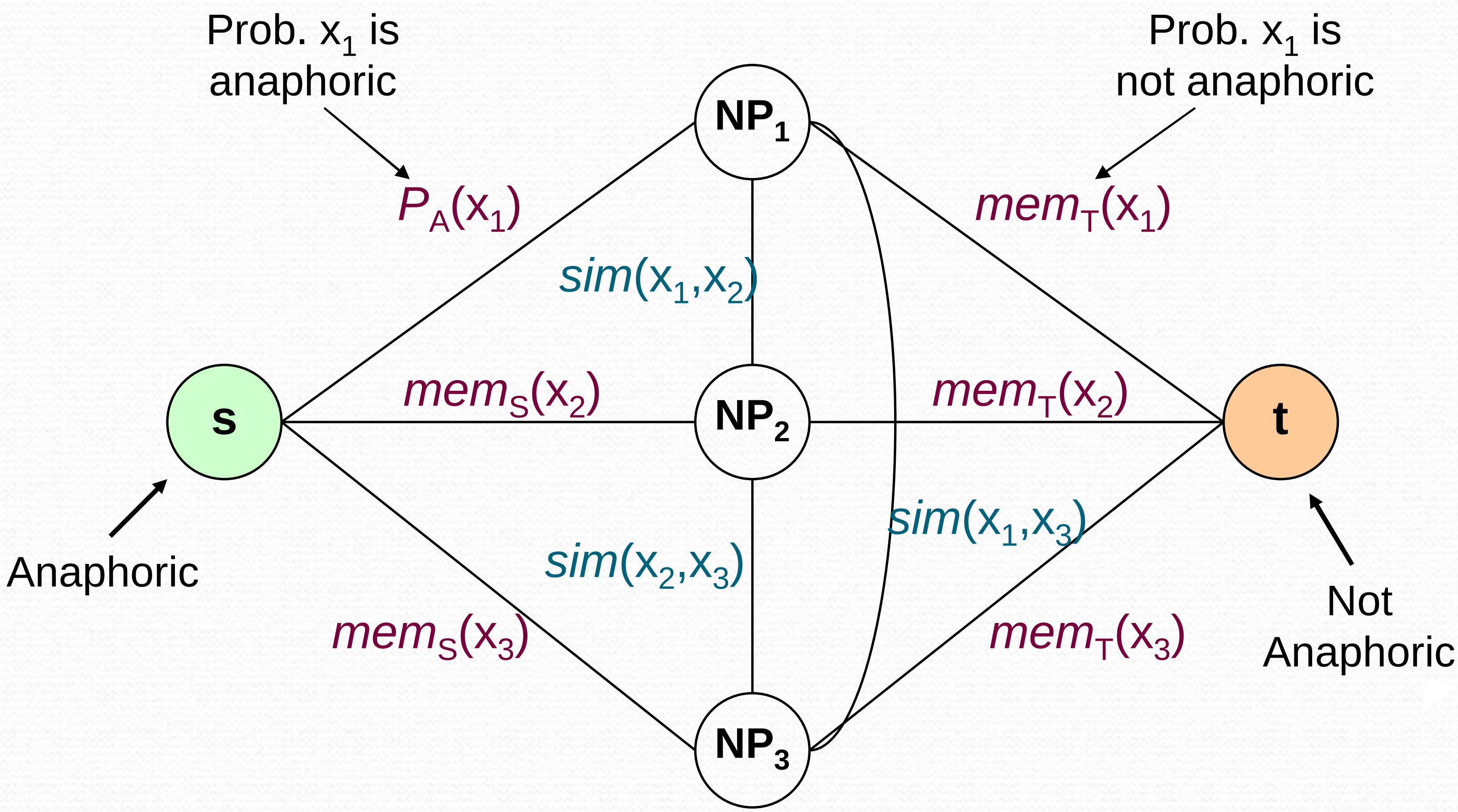

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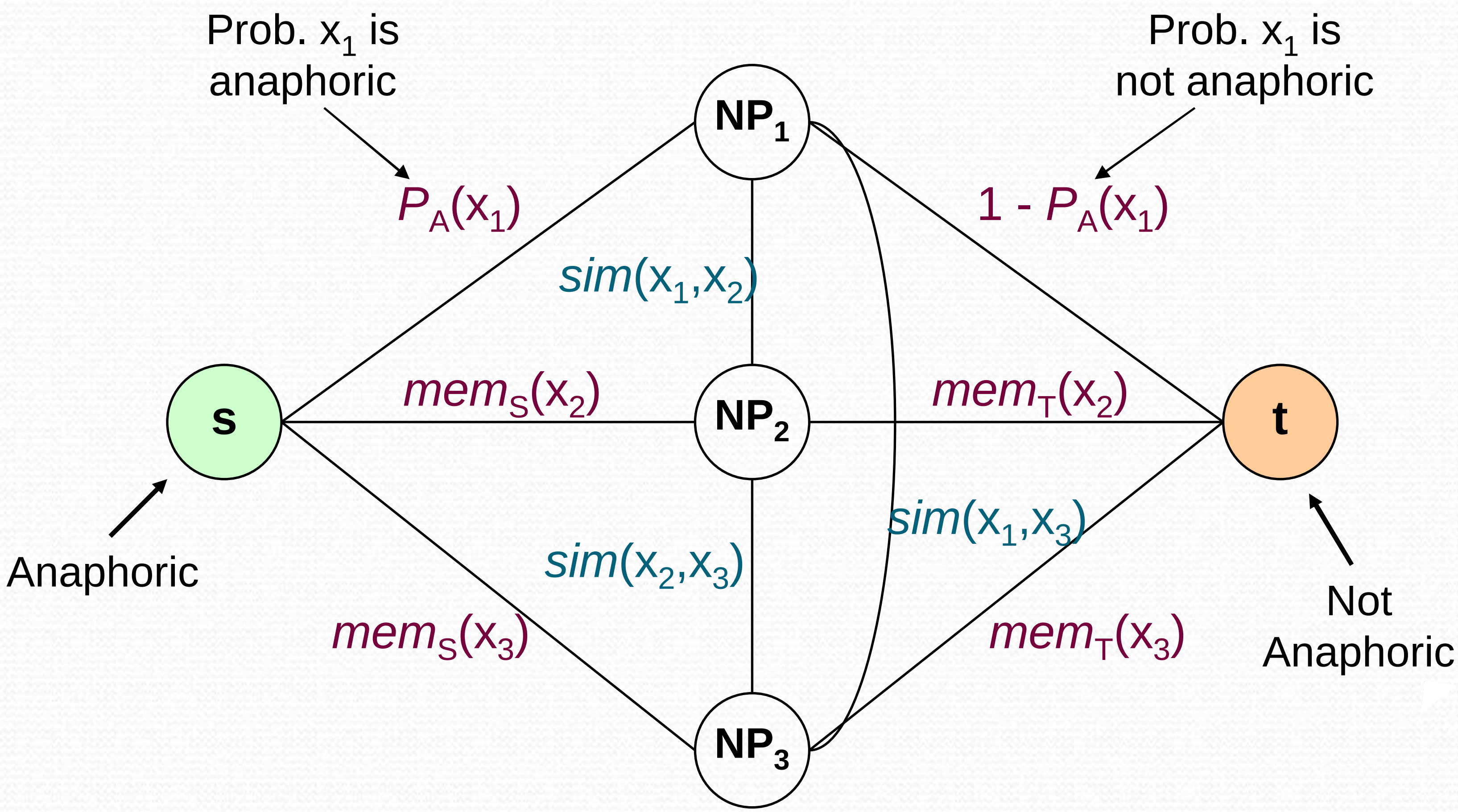

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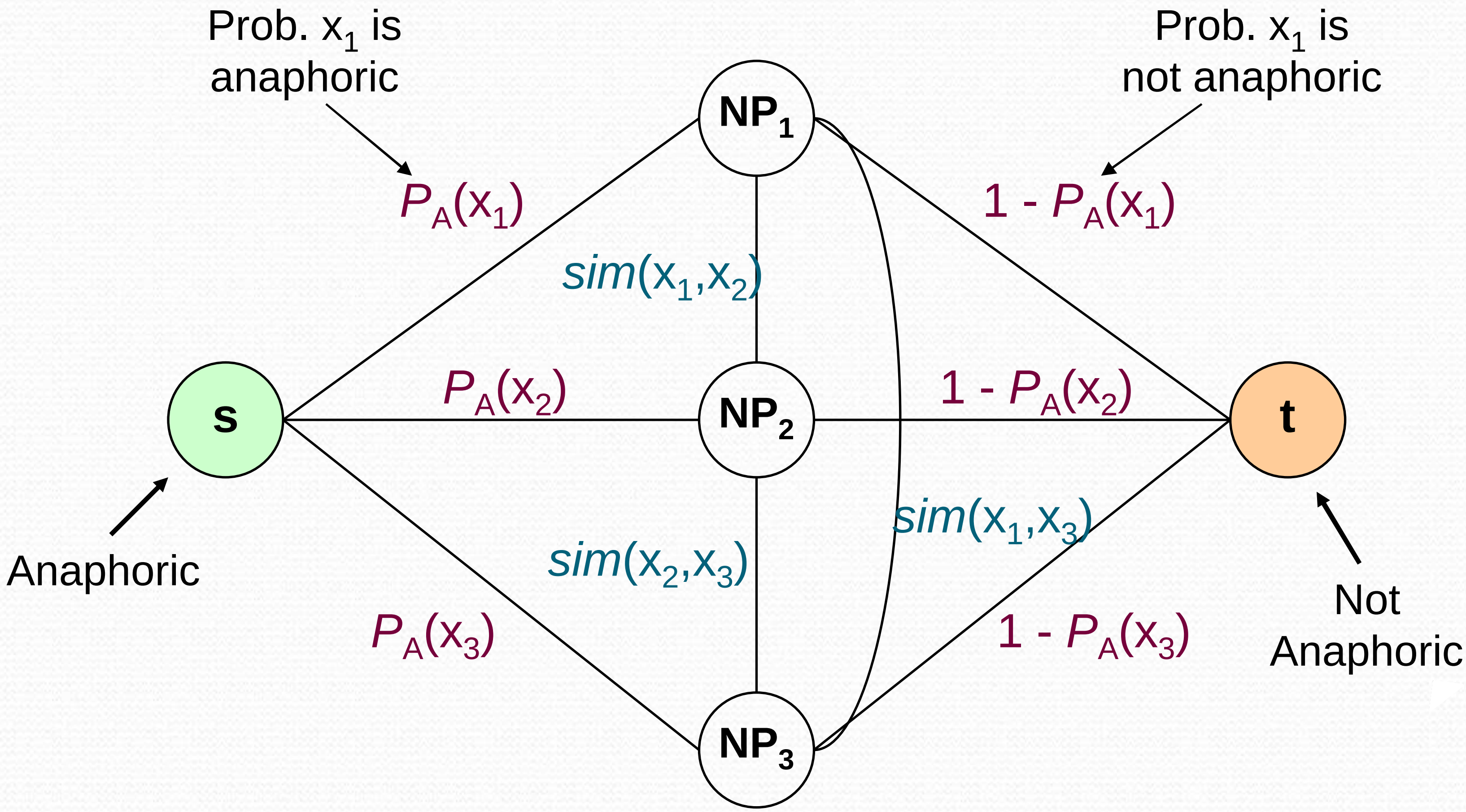

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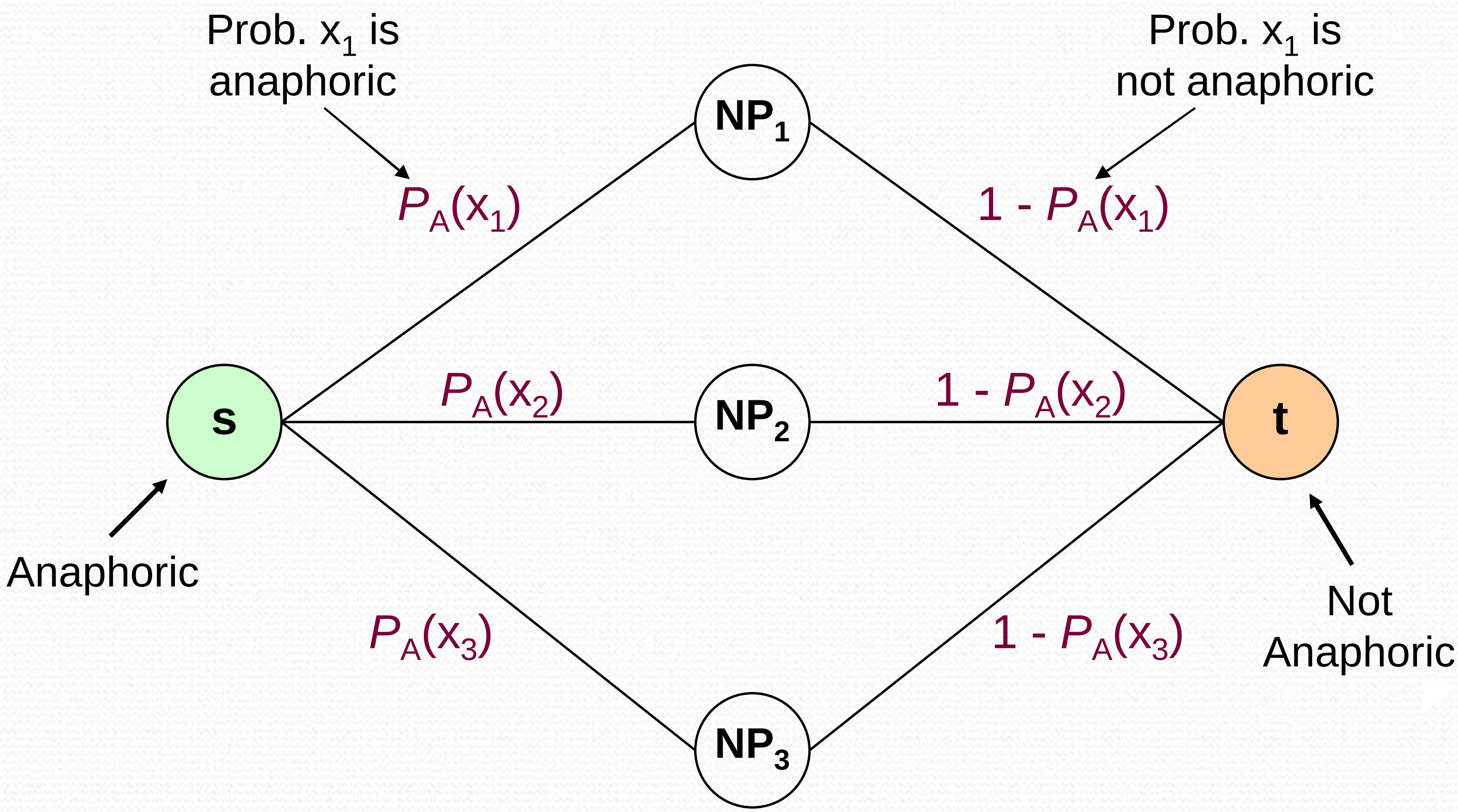
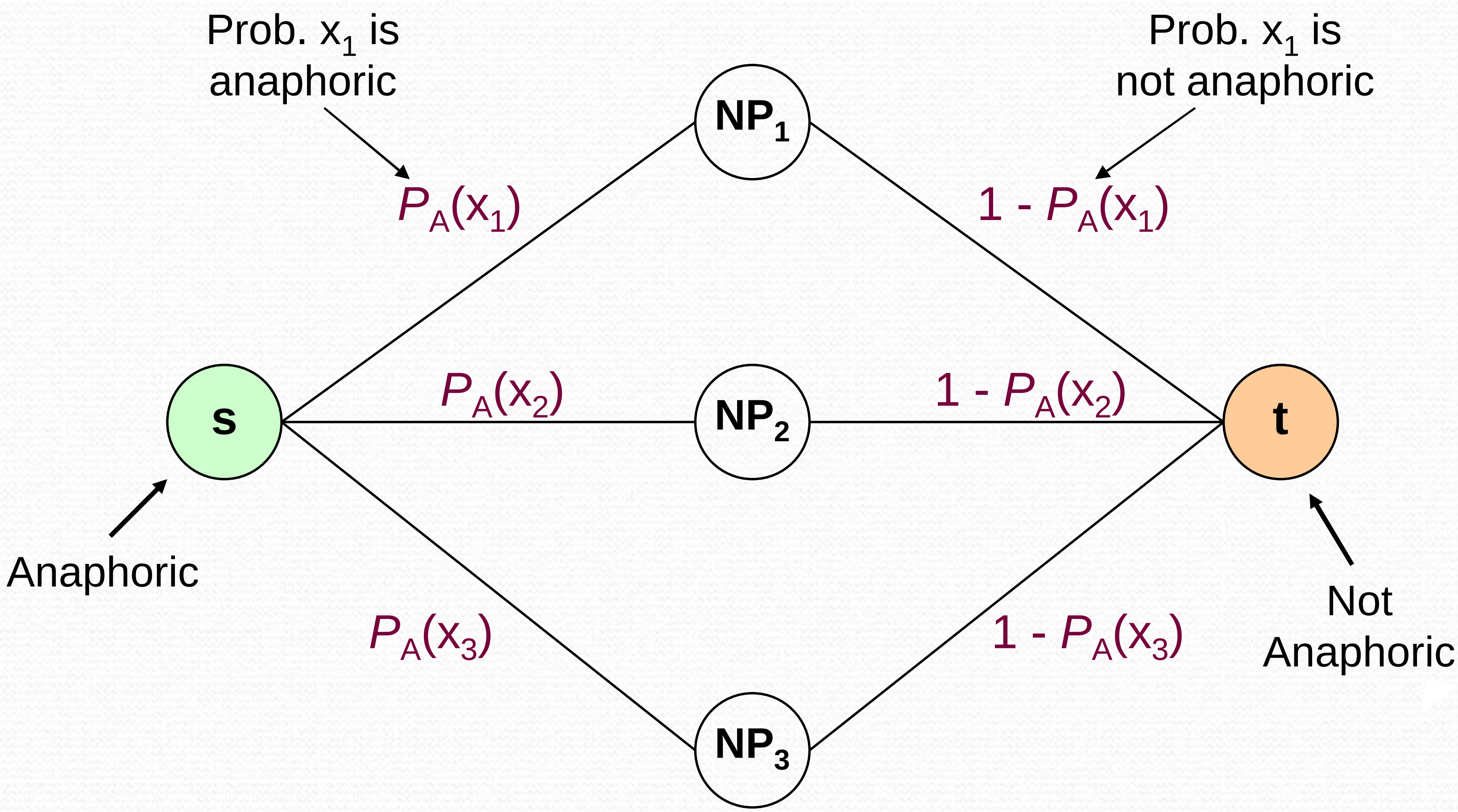


Cut-Based Anaphori

What if we run the mincut finding algorithm on this graph?



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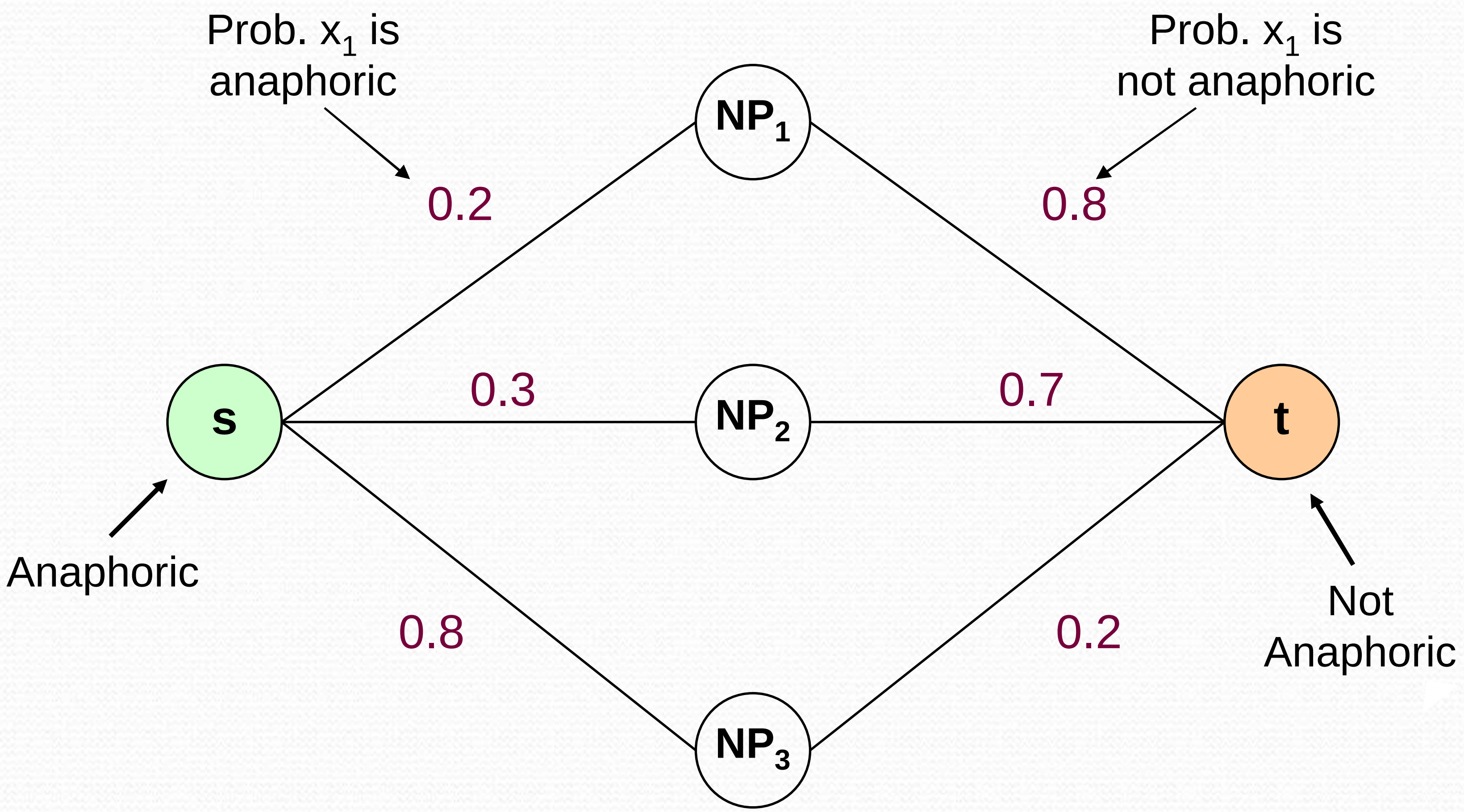

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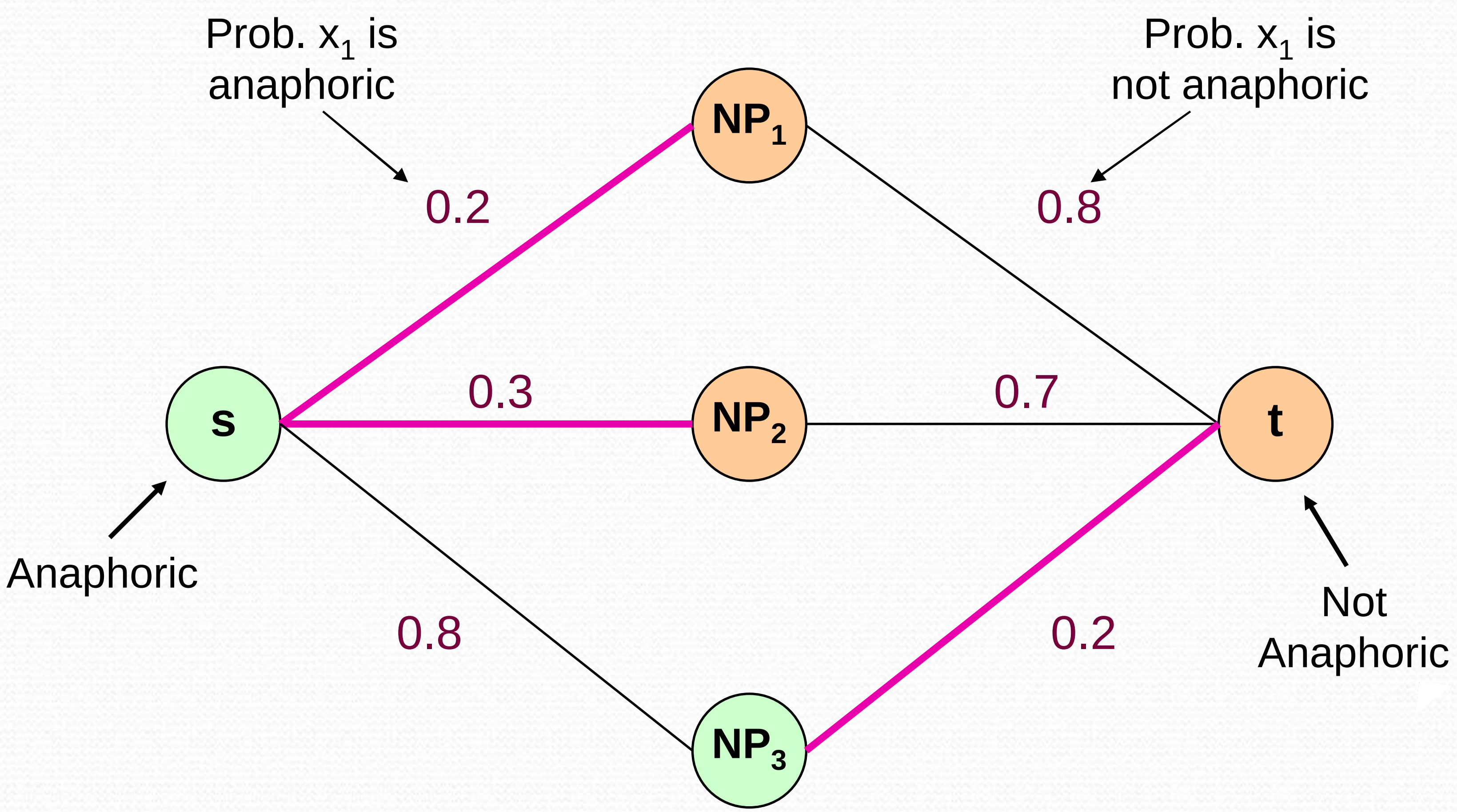

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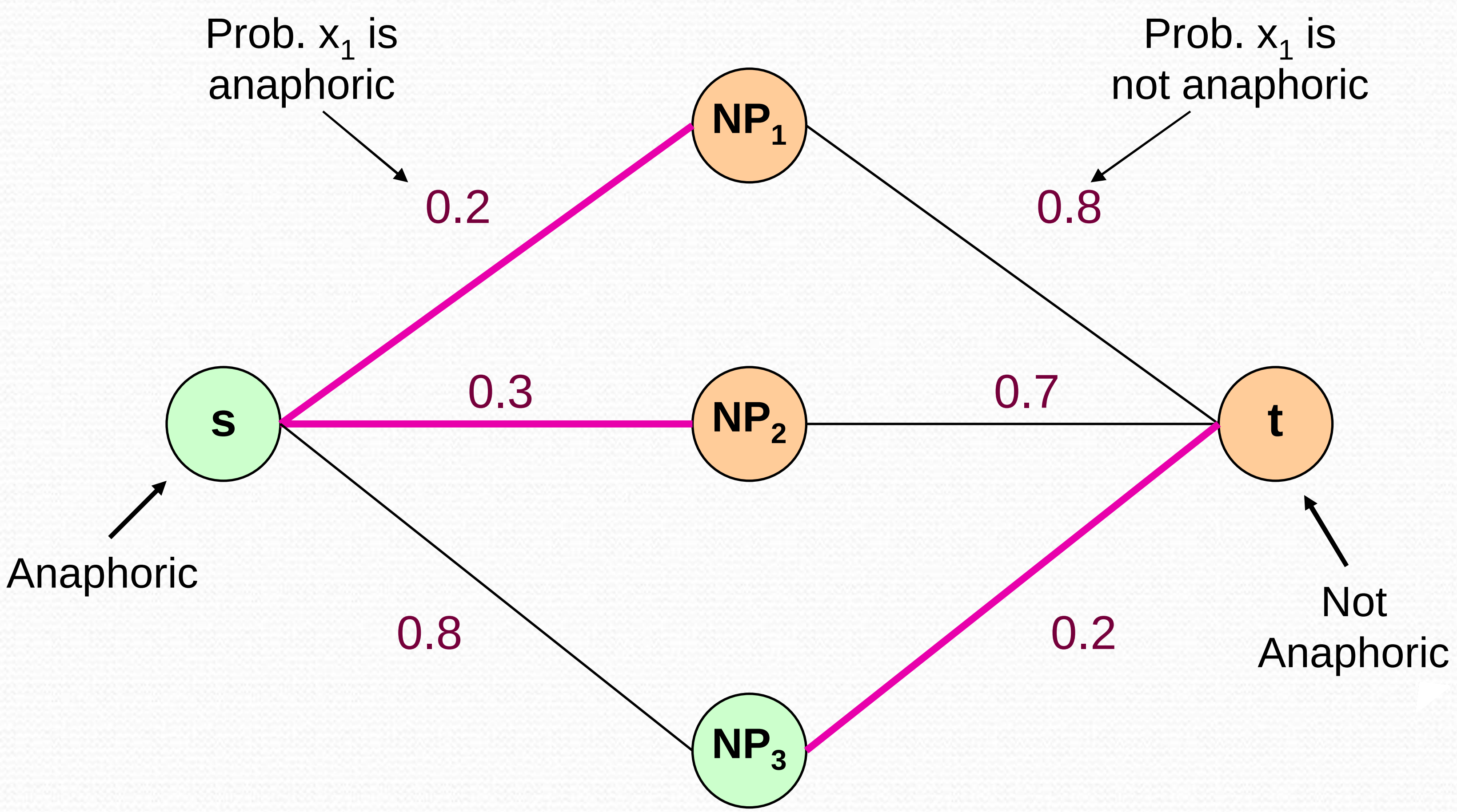
NP$_i$ will be assigned to the Anaphoric class iff $P_A(NP_i) \geq 0.5$



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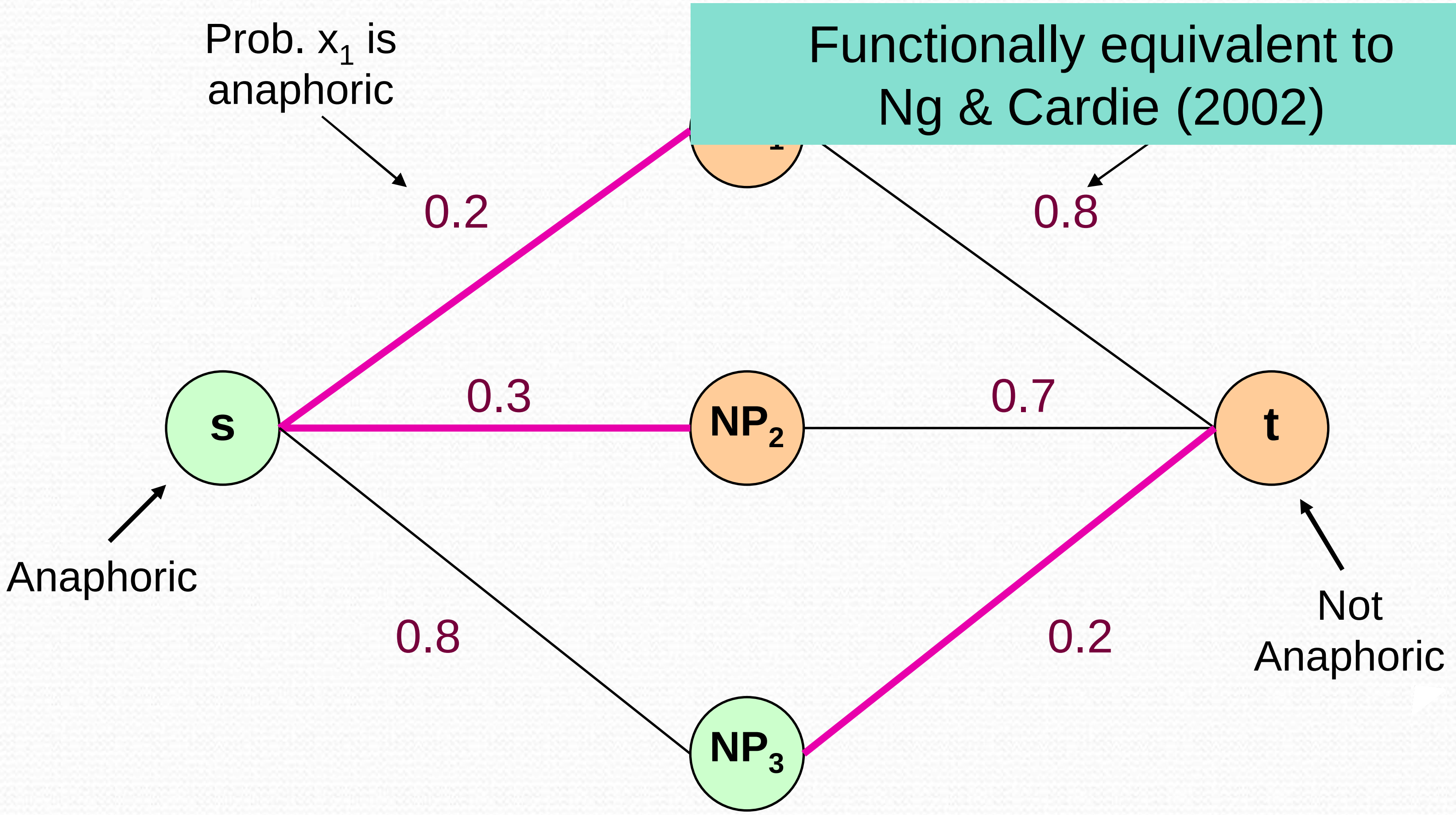

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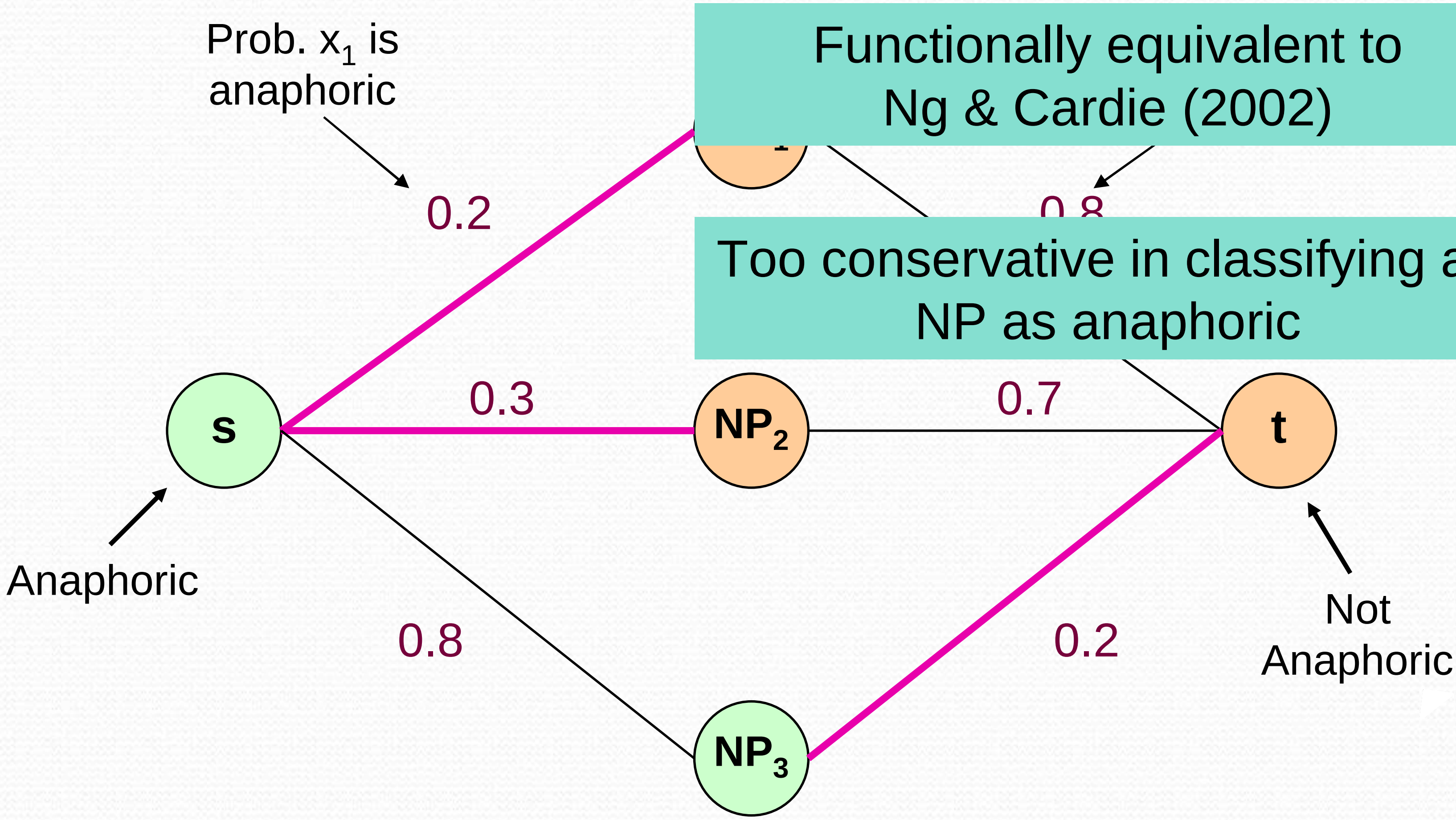

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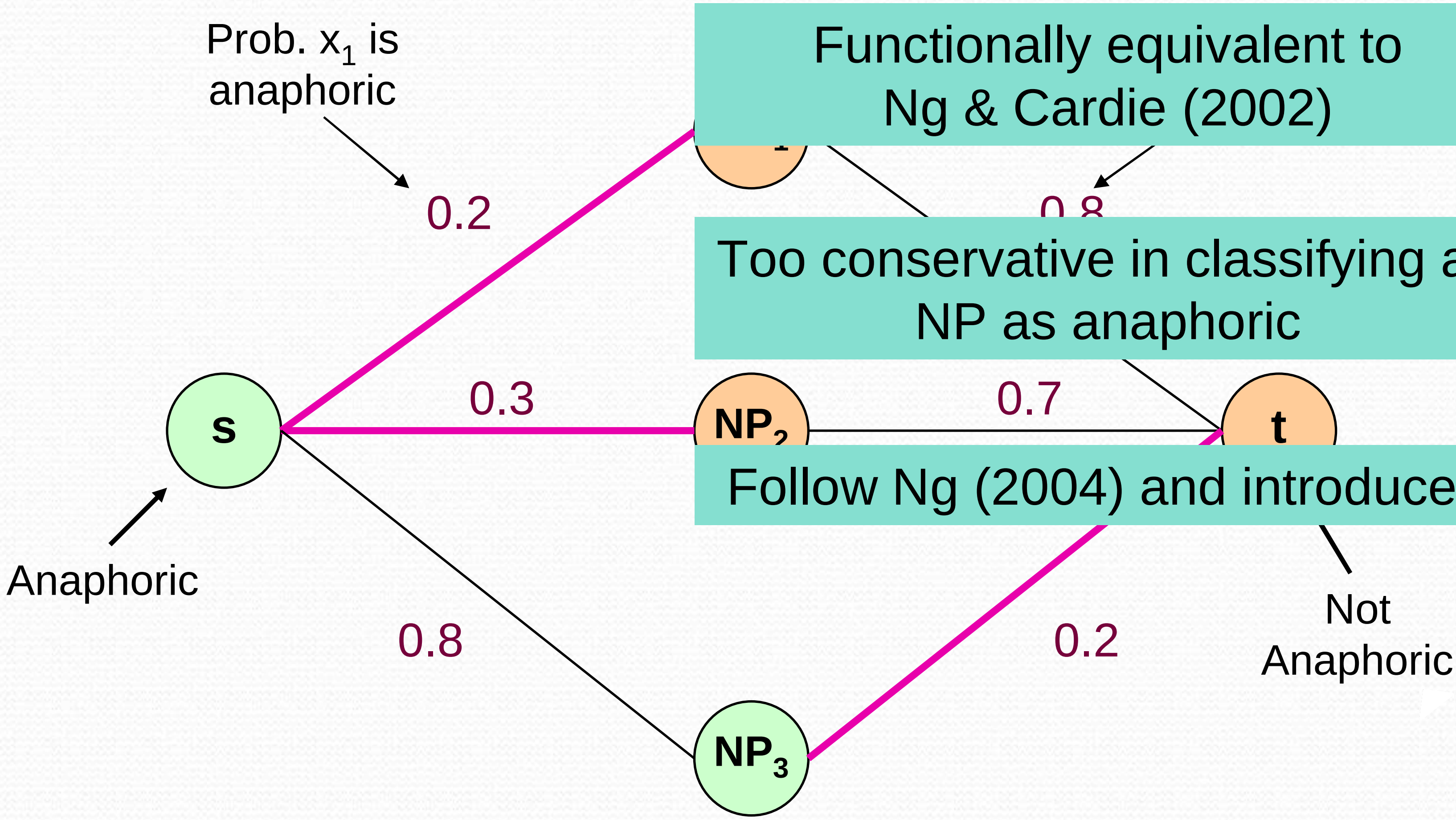
Follow Ng (2004) and introduce ***t***



Mimicking Ng (2004)

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- Goal: modify the edge weights s.t. NP_i will be assigned to the Anaphoric class iff $\mathbf{P_A}(NP_i) \geq \boldsymbol{t}$
- How? Do a linear transformation
- But … we are not happy with just mimicking Ng (2004)

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- What is a good candidate similarity function?

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- Otherwise, set $sim(NP_i, NP_j)$ to 0

Cut-Based Anaphoricity Determination

- An anaphoricity determination method that can
  - maximize the desired coreference metric (by tuning $\boldsymbol{t}$ and $\boldsymbol{t}_2$)
  - exploit probabilities provided by $\mathbf{P_C}$ (via the *sim* function)

Plan for the Talk

- Existing methods for computing and using anaphoricity info
- Our graph-cut-based approach to anaphoricity determination
- Evaluation

Evaluation: Goal

- compare our cut-based method for anaphoricity determination with existing methods w.r.t. their effectiveness in improving a learning-based coreference system

Experimental Setup

- Coreference system [Ng, 2007]
  - implements the standard machine learning framework
  - 34 features per instance
- Features for anaphoricity determination [Ng & Cardie, 2002]
  - 37 features per instance
- Learning algorithm
  - Maximum entropy for training $\mathbf{P_A}$ and $\mathbf{P_C}$

Experimental Setup (Cont')

- The ACE coreference corpus
  - 3 data sets (Broadcast News, Newspaper, Newswire)
  - each data set comprises a training set and a test set
- NPs extracted automatically
- Scoring programs
  - MUC (Vilain et al., 1995) and CEAF (Luo, 2005)
    - recall, precision, F-measure

CEAF Results: “No Anaphoricity” Baseline

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
No anaphoricity	63.2	49.2	**55.3**	64.5	54.3	**59.0**	67.3	56.1	**61.2**

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- F-measure drops slightly in all cases
  - large drops in recall accompanied by smaller gains in precision
  - many anaphoric NPs were misclassified

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	R	P	F	R	P	F	R	P	F
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- requires tuning of ***t***
  - reserve 1/3 of the training data for parameter tuning
  - train $\mathbf{P}_A$ and $\mathbf{P}_C$ on remaining 2/3 of the training data

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- requires tuning of ***t***
  - reserve 1/3 of the training data for parameter tuning
  - train $\mathbf{P_A}$ and $\mathbf{P_C}$ on remaining 2/3 of the training data
- mixed results in comparison to “No Anaphoricity” baseline
  - F-measure gains by 0.2% for BNEWS, 1.1% for NPAPER, but drops by 0.6% for NWIRE

CEAF Results: Luo (2007) Baseline

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
No anaphoricity	63.2	49.2	**55.3**	64.5	54.3	**59.0**	67.3	56.1	**61.2**
Ng & Cardie (2002)	55.9	53.3	**54.5**	60.7	56.3	**58.3**	60.6	58.2	**59.4**
Ng (2004)	62.5	49.9	**55.5**	63.5	57.0	**61.0**	65.6	56.3	**60.6**
Luo (2007)	62.7	51.1	**56.3**	64.6	55.4	**59.6**	67.0	56.8	**61.5**

CEAF Results: Luo (2007) Baseline

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
No anaphoricity	63.2	49.2	**55.3**	64.5	54.3	**59.0**	67.3	56.1	**61.2**
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- in comparison to "No Anaphoricity" baseline
  - F-measure improves insignificantly (by 0.3-1.0%)

Results: Denis & Baldridge (2007) Baseline

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
No anaphoricity	63.2	49.2	**55.3**	64.5	54.3	**59.0**	67.3	56.1	**61.2**
Ng & Cardie (2002)	55.9	53.3	**54.5**	60.7	56.3	**58.3**	60.6	58.2	**59.4**
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Denis & Baldridge (2007)	63.8	51.4	**56.9**	62.6	53.6	**57.8**	67.0	56.8	**61.5**

Results: Denis & Baldridge (2007) Baseline

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	R	P	F	R	P	F	R	P	F
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- mixed results in comparison to “No Anaphoricity” baseline
  - F-measure rises significantly for BNEWS, drop insignificantly for NPAPER, and rises insignificantly for NWIRE

CEAF Results: Kleener (2007) Baseline

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
No anaphoricity	63.2	49.2	**55.3**	64.5	54.3	**59.0**	67.3	56.1	**61.2**
Ng & Cardie (2002)	55.9	53.3	**54.5**	60.7	56.3	**58.3**	60.6	58.2	**59.4**
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Kleener (2007)	63.2	51.3	**56.7**	62.6	53.6	**57.8**	66.7	56.7	**61.3**

- in comparison to Denis & Baldridge baseline,
  - F-measure never improves, recall slightly deteriorates
  - transitivity constraints tend to produce smaller clusters
  - enforcing transitivity does not improve coreference performance

CEAF Results: Graph Minimum Cut

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
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Graph Minimum Cut	61.4	57.6	**59.4**	64.1	59.4	**61.7**	65.7	61.9	**63.8**

- 1/3 of training data for joint tuning of t and t_2; 2/3 for training $\mathbf{P_A}$ and $\mathbf{P_C}$

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Kleener (2007)	63.2	51.3	**56.7**	62.6	53.6	**57.8**	66.7	56.7	**61.3**
Graph Minimum Cut	61.4	57.6	**59.4**	64.1	59.4	**61.7**	65.7	61.9	**63.8**

- 1/3 of training data for joint tuning of t and t_2; 2/3 for training $\mathbf{P_A}$ and $\mathbf{P_C}$
- significant improvement over "No Anaphoricity" baseline
  - large gains in precision and smaller drops in recall

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	Broadcast News			Newspaper			Newswire		
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Graph Minimum Cut	61.4	57.6	**59.4**	64.1	59.4	**61.7**	65.7	61.9	**63.8**

- 1/3 of training data for joint tuning of t and t_2; 2/3 for training $\mathbf{P_A}$ and $\mathbf{P_C}$
- significant improvement over "No Anaphoricity" baseline
  - large gains in precision and smaller drops in recall
- significant improvement over best baseline (D&B)

CEAF Results: Graph Minimum Cut

	Broadcast News			Newspaper			Newswire		
	R	P	F	R	P	F	R	P	F
No anaphoricity	63.2	49.2	**55.3**	64.5	54.3	**59.0**	67.3	56.1	**61.2**
Ng & Cardie (2002)	55.9	53.3	**54.5**	60.7	56.3	**58.3**	60.6	58.2	**59.4**
Ng (2004)	62.5	49.9	**55.5**	63.5	57.0	**61.0**	65.6	56.3	**60.6**
Luo (2007)	62.7	51.1	**56.3**	64.6	55.4	**59.6**	67.0	56.8	**61.5**
Denis & Baldridge (2007)	63.8	51.4	**56.9**	62.6	53.6	**57.8**	67.0	56.8	**61.5**
Kleener (2007)	63.2	51.3	**56.7**	62.6	53.6	**57.8**	66.7	56.7	**61.3**
Graph Minimum Cut	61.4	57.6	**59.4**	64.1	59.4	**61.7**	65.7	61.9	**63.8**

- 1/3 of training data for joint tuning of t and t_2; 2/3 for training $\mathbf{P_A}$ and $\mathbf{P_C}$
- significant improvement over “No Anaphoricity” baseline
  - large gains in precision and smaller drops in recall
- significant improvement over best baseline (D&B)
- best F-measure score achieved for each dataset

Summary

- Proposed a graph-cut-based approach to anaphoricity determination that
  - directly optimizes the desired coreference evaluation metric
  - exploits the probabilities provided by the coreference model
  - achieves the best results on all three ACE datasets according to both the MUC scorer and the CEAF scorer
  - provides a flexible mechanism for co-ordinating anaphoricity and coreference decisions