2007/02/18-24, CICLing-2007

Latent Variable Models for Causal Knowledge Acquisition

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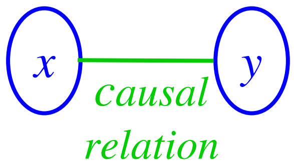
Background & Research Goral (1/5)

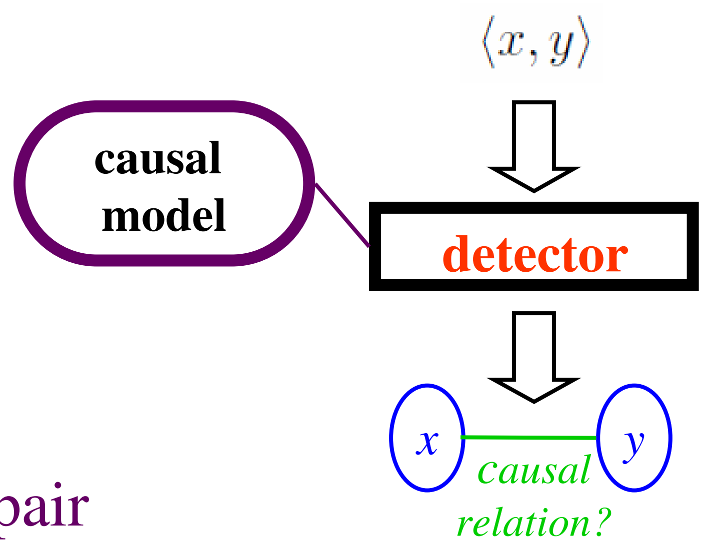
- In the fileds of AI and NLU,
  some applications need inference rules or knowledge of causal relations.
  - Question answering system
  - Dialog system

- Constructing causal models (causality detectors)
  for acquiring knowledge of causal relations is one central issue.



Background & Research Goral (2/5)

- **Causality detector** based on a causal model
  - Input: an event pair $\langle x, y \rangle$
    - Extracted from text documents



  - Output: Yes/No label
    - Yes: Holding causal relations between the input event pair
    - No: Not holding

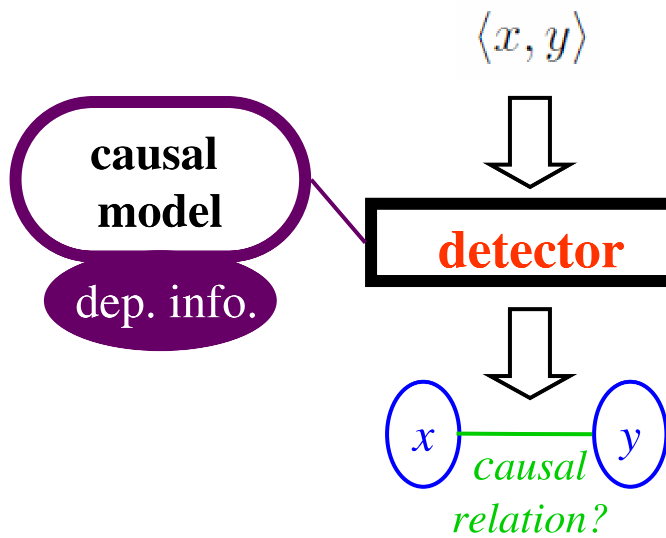
$$\hat{c} = argmax_{c_m} P(c_m | x, y)$$

Background & Research Goral (3/5)

Although

the concept "*causal relation*" is difficult to understand,

- Causal relations are assumed to be a subclass of general dependency relations.



- Causal models need to capture the dependency information between (input) event pairs.

Background & Research Goral (4/5)

dep. info.

- Two approaches for capturing dependency info.
  - Cue-phrase-based approach
    - Using cue-phrases such as “because” and “since”
    - Unable to treat event pairs **without** cue phrases
    - Medium precision, but very low coverage △
  - Statistical approach
    - Using co-occurrence statistics of event pairs
    - Independent of cue phrases
    - Keeping precision, and achieving higher coverage ◎

Background & Research Goral (5/5)

- [Chang et al. 2004]
  - One of the state-of-the art statistical models for causality detection
    - Based on naïve bayes assumption
    - Hard to capture the dependency info
      - » Critical to improve the performance of the causality detection

Our research goal is to resolve this problem.

We propose new statistical models for causality detection.

New models (1/5)

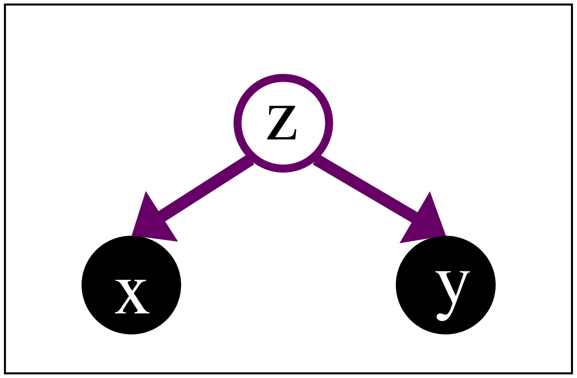
- Expanded versions of the statistical co-occurrence models proposed by [Hofmann et al. 1998]

We adopted the co-occurrence models as the bases of the new models from the observation:

If two events are holing causal relation,
these events tend to co-occur in text.

New models -- [Hofmann et al. 1998]

- **Aspect**
  - **Graphical representation of statistical dependency**



X : cause event (observed)

Y : effect event (observed)

Z : latent variable (unobserved)

$$P(x,y) = \sum_z P(x|z)P(y|z)P(z)$$

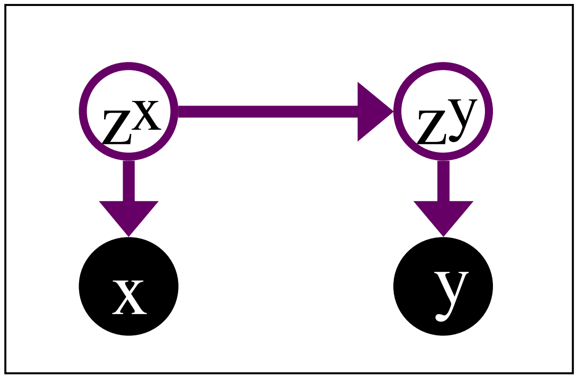
- **Z** represents semantic clusters shared by **X** and **Y**.

⬇

- The dependency info. can be captured through **Z**.

New models -- [Hofmann et al. 1998]

Product



$$P(x,y) = \sum_{z^x,\, z^y} P(x|z^x)P(y|z^y)P(z^y|z^x)P(z^x)$$

- Almost the same as **aspect,**

- Differences
  - Two latent variables $\mathbf{Z}^{\mathbf{x}}$ and $\mathbf{Z}^{\mathbf{y}}$, and
  - Statistical dependency between them

New models -- [Hofmann et al. 1998]

- Two statistical co-occurrence models
  - **Aspect**
  - **Product**

To summarize, these models

- Able to incorporate dependency information via latent variable(s),
- But, unable to treat causality information (Yes/No label).

Causality information **=** (Yes/No label)

Output: Yes/No label

Yes: Holding causal relations between the input event pair

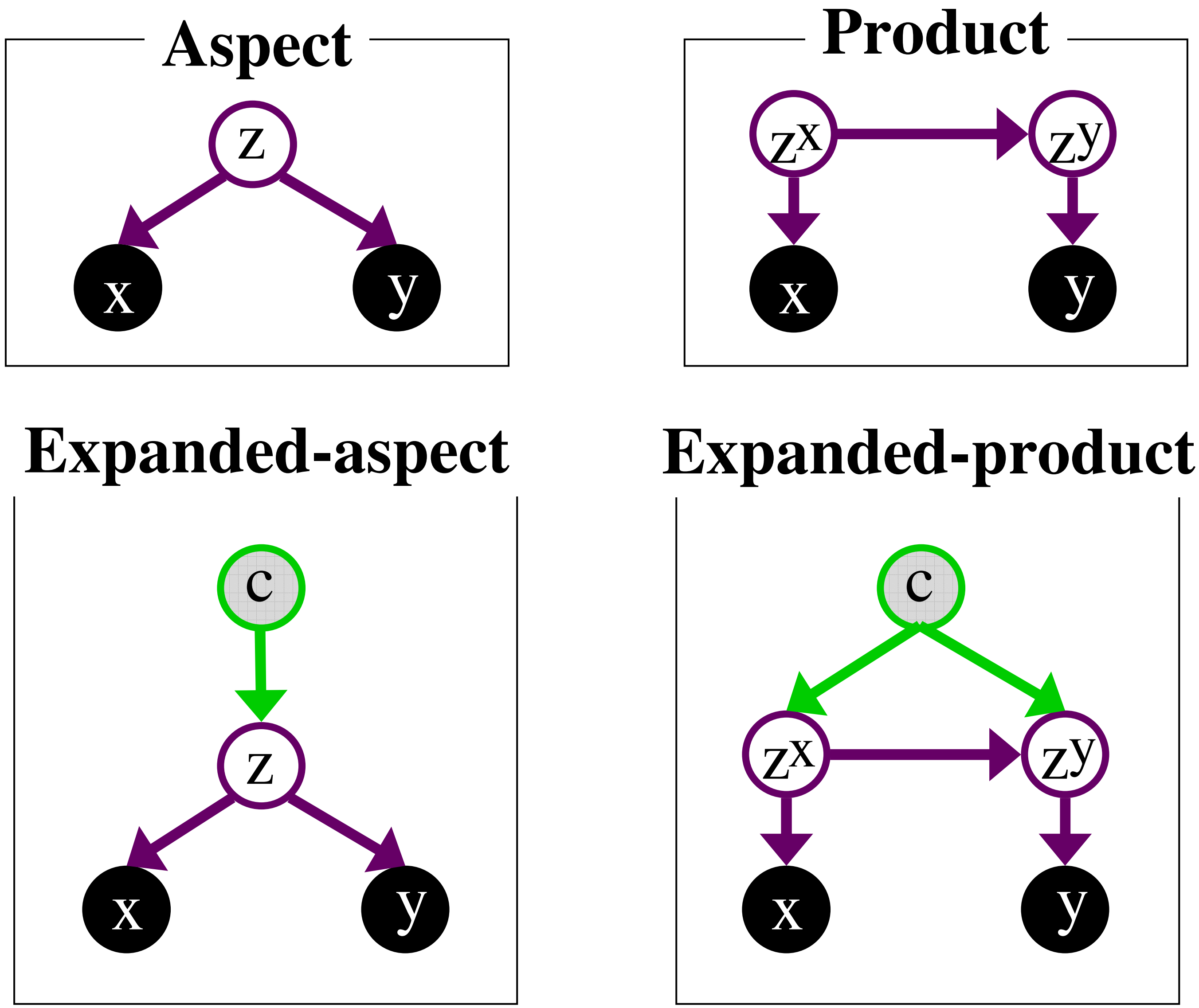
No: Not holding

We introduce a random variable ***C*** to **Aspect** and **Product** models.

(The solution is direct and very simple !!)

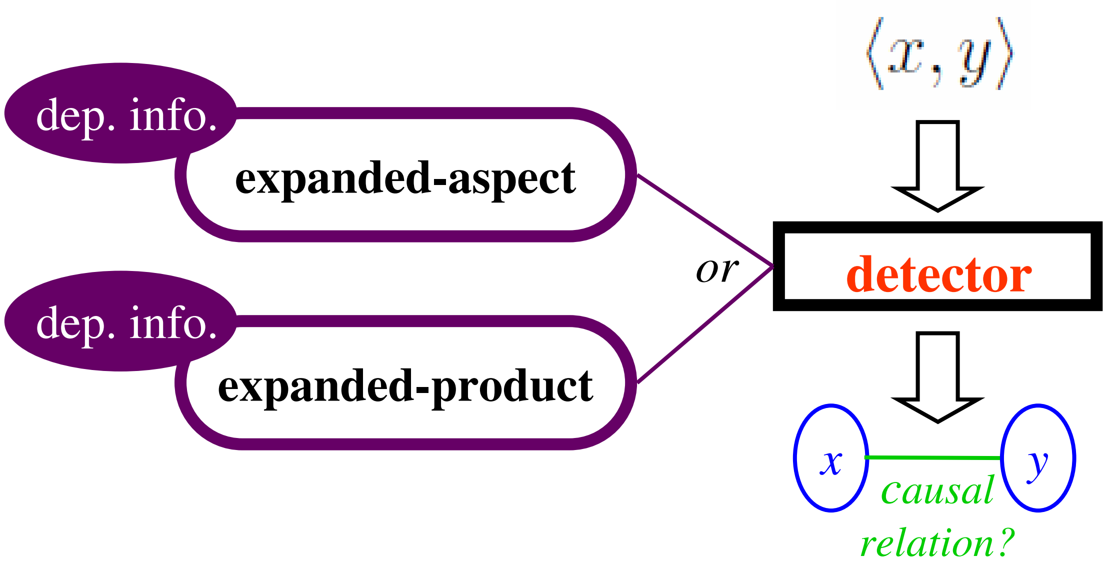
- **Expanded-aspect**
- **Expanded-product**

New models (2/5)



New models (3/5)

- Causality detector based on the new model
  - Input: $\langle x, y \rangle$
  - Output: $\hat{c} = argmax_{c_m} \boxed{P(c_m | x, y)}$



New models (4/5)

- **Causality detector** based on the new model
  - Input: $\langle x, y \rangle$
  - Output: $\hat{c} = argmax_{c_m} \boxed{P(c_m|x,y)}$

P(c_m | x , y)

expanded-aspect

$$P(c_m|x,y) = \frac{\sum_{z_k} P(x|z_k)P(y|z_k)P(z_k|c_m)P(c_m)}{\sum_{z_k,c_m} P(x|z_k)P(y|z_k)P(z_k|c_m)P(c_m)}$$

expanded-product

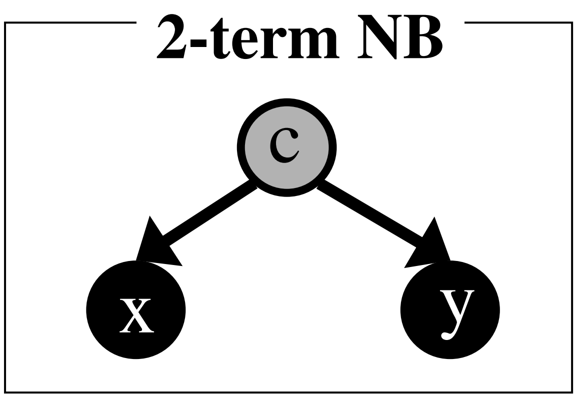
$$P(c_m|x,y) = \frac{\sum_{z_k^x,z_l^y} P(x|z_k^x)P(y|z_l^y)P(z_k^x|c_m)P(z_l^y|z_k^x,c_m)P(c_m)}{\sum_{z_k^x,z_l^y,c_m} P(x|z_k^x)P(y|z_l^y)P(z_k^x|c_m)P(z_l^y|z_k^x,c_m)P(c_m)}$$

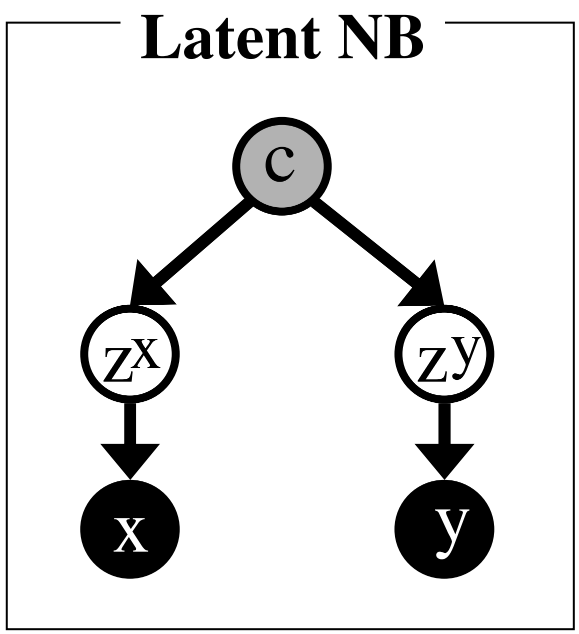
New models (5/5)

- Parameter estimation of the models
  - Maximum likelihood estimates from both a set of event pairs $\langle x, y \rangle$ and a set of triplets $\langle x, y, \underbrace{c}_{\text{Yes/No label}} \rangle$
  - Use EM algorithm [Dempster et al. 1977]
    - Follow the methods [Nigam et al. 2000] and [Hofmann 2001]

Experiment

- Effectiveness of incorporating dependency info.
  - 4 models
    - **Expanded-aspect**, **Expanded-product**
    - **2-term NB** [Mitchell 1997], **Latent NB** [Zhang et al. 2004]
      - » Baseline models. No dependency info.





Experiment

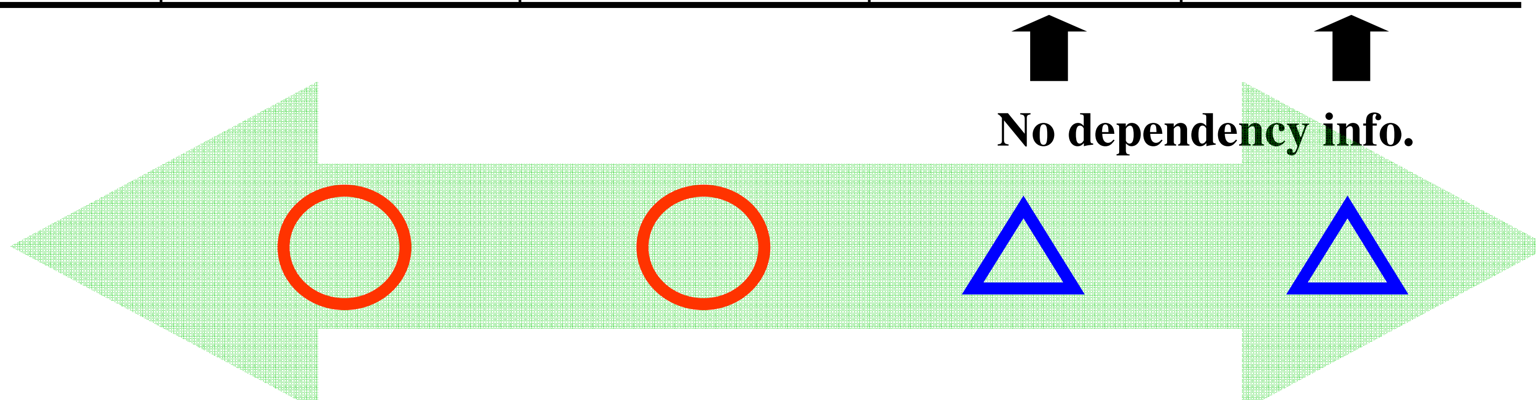
- Effectiveness of incorporating dependency info.
  - 4 models
    - **Expanded-aspect**, **Expanded-product**
    - **2-term NB** [Mitchell 1997]**,** **Latent NB** [Zhang et al. 2004]
      - Baseline models. No dependency info.
  - Data
    - Japanese newspaper text
      - 400 triplets [Inui et al. 2005]
      - Event pairs (0 pairs / 100 pairs / 1,000 pairs / 10,000 pairs)
      - Verb-pair which has a syntactic dependency relation

        (A precise modeling of events will be addressed in the future)
  - 5-fold cross validation

Experiment

(*F*-measure)

		expanded-aspect	**expanded-product**	**NB**	**LNB**
# of event pairs	0	.319	.583	.298	.533
	100	.588	.610	.328	.569
	1,000	.644	.641	.459	.595
	10,000	.677	.678	.623	.631



Conclusion

- We proposed statistical models for detecting causality between an input event pair
- Our causal models
  - Based on statistical co-occurrence models
  - Kinds of latent variable models
  - Able to treat supervised label information via a class variable
- We demonstrated that our models
  - Outperformed the baseline models, and
  - Achieved .678 *F*-measure value

Thank you!