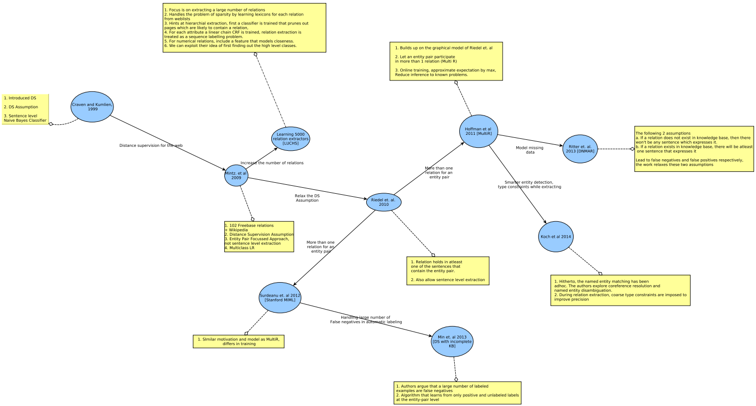
# Distant Supervision Techniques

- First paper in 1999, almost every possibility explored



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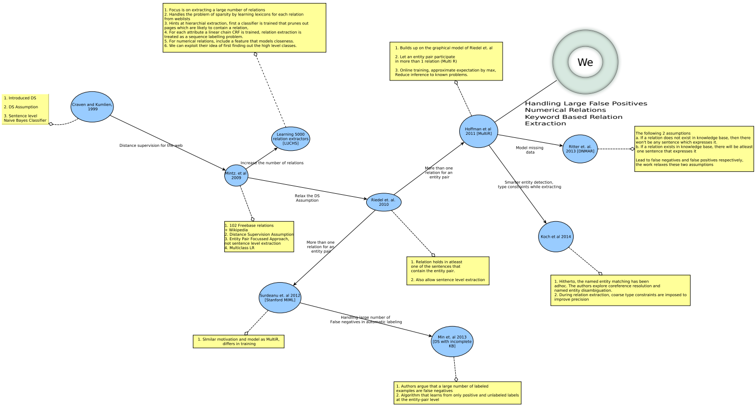
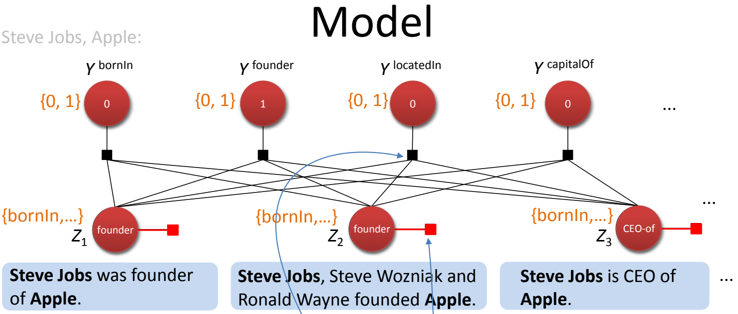


# Relation Extraction Using MultiR

From `raphaelhoffmann.com/publications`




$$p(\mathbf{Y}=\mathbf{y},\mathbf{Z}=\mathbf{z}|\mathbf{x};\theta) \stackrel{\text{def}}{=} \frac{1}{Z_x}\prod_r \Phi^{\text{join}}(y^r,\mathbf{z})\prod_i \Phi^{\text{extract}}(z_i,x_i)$$

$$\Phi^{\text{join}}(y^r,\mathbf{z}) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if } y^r = true \wedge \exists i : z_i = r \\ 0 & \text{otherwise} \end{cases}$$

All features at sentence-level

(join factors are deterministic ORs)

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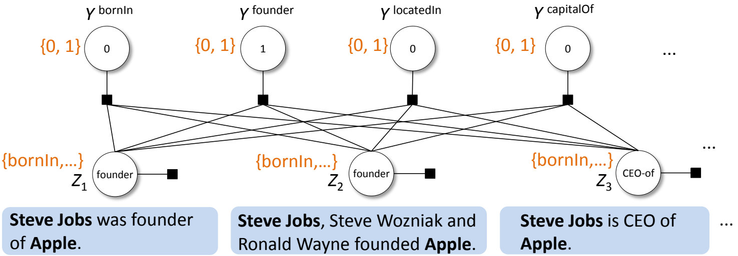
## Model




- Extraction almost entirely driven by sentence-level reasoning
- Tying of facts $Y_r$ and sentence-level extractions $Z_i$ still allows us to model weak supervision for training

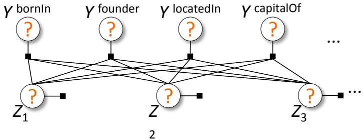
# Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

## Inference

Need:

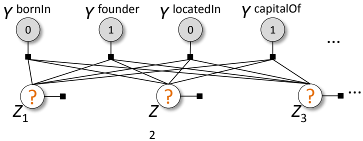
- Most likely sentence labels:




$$\arg\max_{\mathbf{y},\mathbf{z}} p(\mathbf{y},\mathbf{z}|\mathbf{x};\theta)$$

**Easy**

- Most likely sentence labels *given* facts:




$$\arg\max_{\mathbf{z}} p(\mathbf{z}|\mathbf{x},\mathbf{y};\theta)$$

**Challenging**

# Relation Extraction Using MultiR

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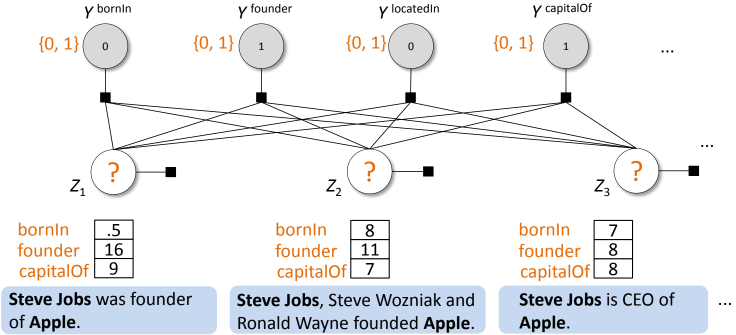
## Inference

- Computing $\arg\max_{\mathbf{z}} p(\mathbf{z}|\mathbf{x},\mathbf{y};\theta)$ :



# Relation Extraction Using MultiR

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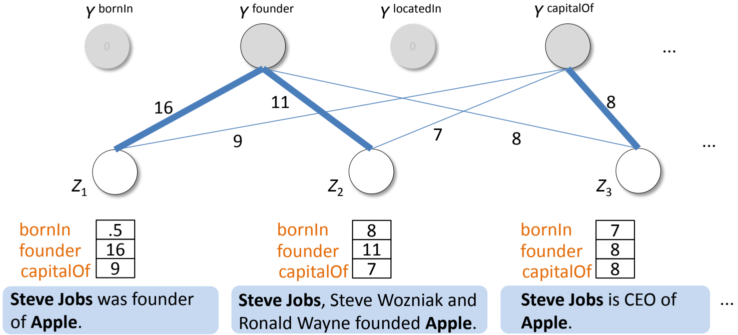
## Inference

- Variant of the weighted, edge-cover problem:



# Learning

- Training set $\{(\mathbf{x}_i, \mathbf{y}_i) | i = 1 \dots n\}$ , where
  - $i$ corresponds to a particular entity pair
  - $\mathbf{x}_i$ contains all sentences with mentions of pair
  - $\mathbf{y}_i$ bit vector of facts about pair from database
- Maximize Likelihood

$$O(\theta) = \prod_i p(\mathbf{y}_i | \mathbf{x}_i; \theta) = \prod_i \sum_{\mathbf{z}} p(\mathbf{y}_i, \mathbf{z} | \mathbf{x}_i; \theta)$$

# Learning

- Scalability: Perceptron-style additive updates
- Requires two approximations:
  1. Online learning
     For example i (entity pair), define
     $$\phi(\mathbf{x}, \mathbf{z}) = \sum_j \phi(x_j, z_j)$$
     Use gradient of local log likelihood for example i:
     $$\frac{\partial \log O_i(\theta)}{\partial \theta_j} = E_{p(\mathbf{z}|\mathbf{x}_i, \mathbf{y}_i; \theta)}[\phi_j(\mathbf{x}_i, \mathbf{z})] - E_{p(\mathbf{y}, \mathbf{z}|\mathbf{x}_i; \theta)}[\phi_j(\mathbf{x}_i, \mathbf{z})]$$
  2. Replace expectations with maximizations

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## Learning: Hidden-Variable Perceptron

passes over dataset

for each entity pair *i*

most likely sentence labels and inferred facts (ignoring DB facts)

most likely sentence labels given DB facts

**initialize** parameter vector $\mathbf{\Theta} \leftarrow \mathbf{0}$

**for** $t = 1 \ldots T$ **do**

  **for** $i = 1 \ldots n$ **do**

    $(\mathbf{y}', \mathbf{z}') \leftarrow \arg\max_{\mathbf{y},\mathbf{z}} p(\mathbf{y}, \mathbf{z} | \mathbf{x_i}; \theta)$

    **if** $\mathbf{y}' \neq \mathbf{y_i}$ **then**

      $\mathbf{z}^* \leftarrow \arg\max_{\mathbf{z}} p(\mathbf{z} | \mathbf{x_i}, \mathbf{y_i}; \theta)$

      $\mathbf{\Theta} \leftarrow \mathbf{\Theta} + \phi(\mathbf{x_i}, \mathbf{z}^*) - \phi(\mathbf{x_i}, \mathbf{z}')$

    **end if**

  **end for**

**end for**

**Return** $\Theta$