# Hyperlink Classification via Structured Graph Embedding

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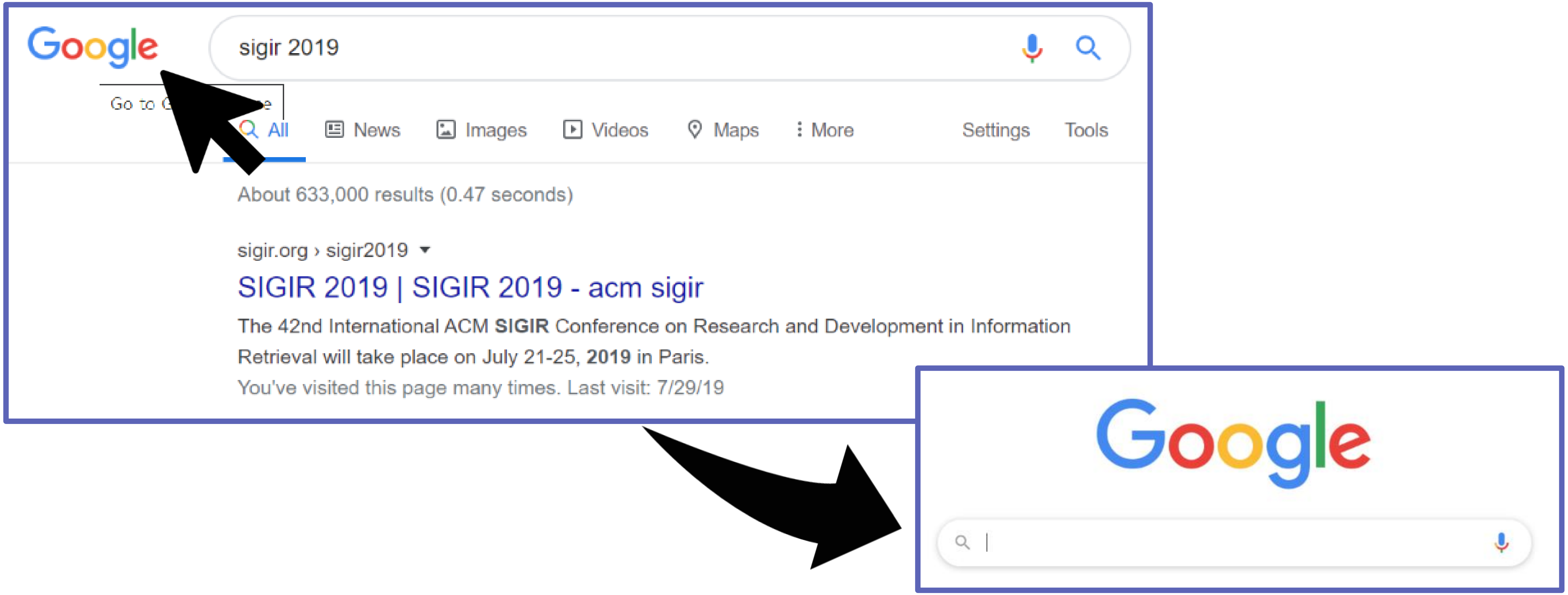
# Real-World Web Graphs

- Hyperlinks are created for different reasons
  - **Navigation links**: navigate the main website
  - **Suggestion links**: suggest users to take a look at related information
  - **Action links**: invoke actions such as ‘edit’, ‘share’, or ‘send an email’

- **Hyperlink Classification Problem**
  - Classify hyperlinks into three classes: navigation, suggestion, and action

# Hyperlink Classification

- ## Navigation Links

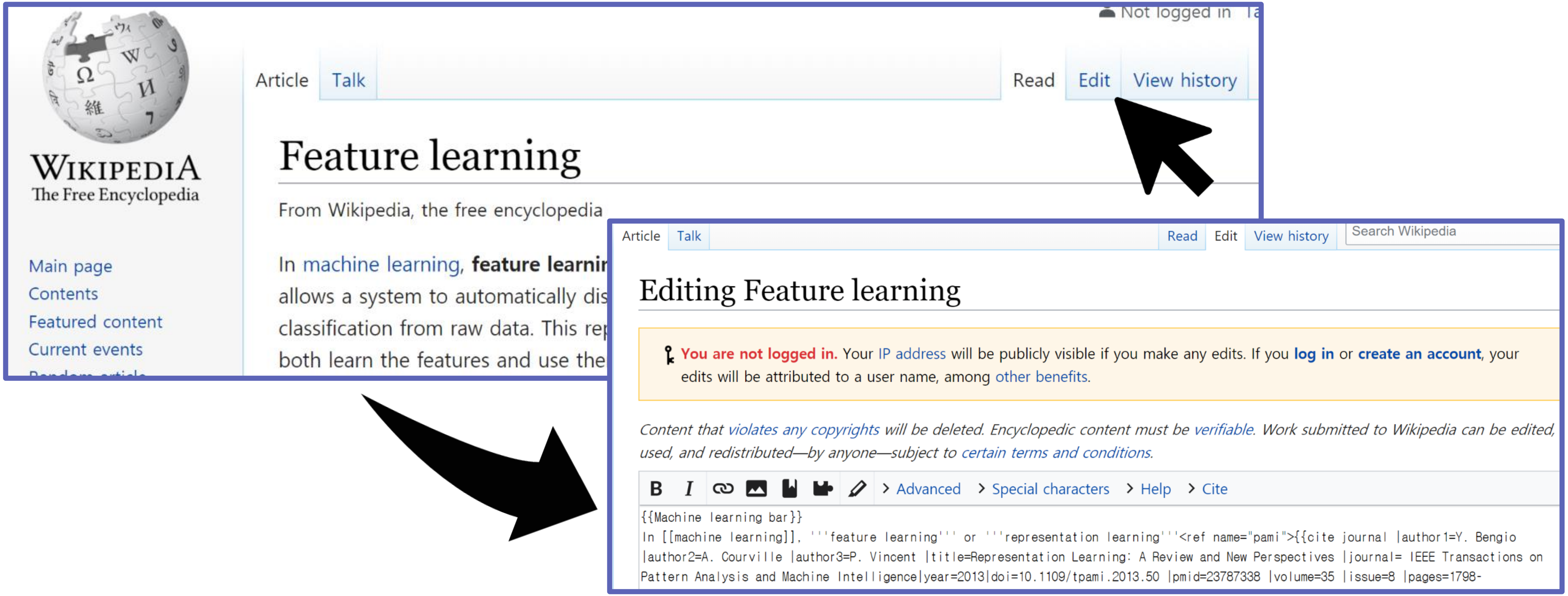


# Hyperlink Classification

- **Suggestion Links**

# Hyperlink Classification

- ## Action Links



# Real-World Datasets

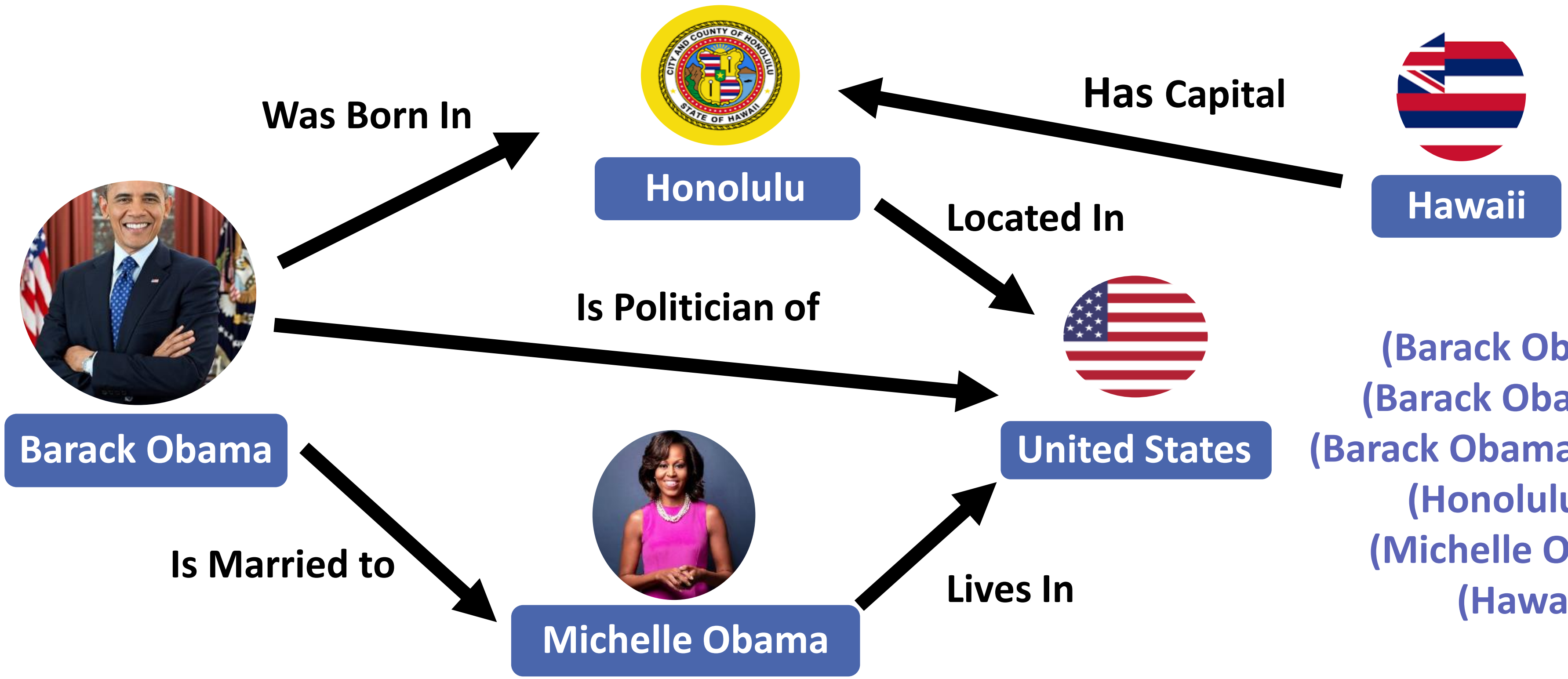
- Real-world web graphs
  - **Crawling** a set of web pages and hyperlinks starting from a page in Stack Overflow.
  - Conducting a **biased random walk**

| | $\lvert\mathcal{V}\rvert$ | $\lvert\mathcal{E}\rvert$ | *navigation* | *suggestion* | *action* |
|---|---|---|---|---|---|
| web_437 | 404 | 437 | 268 (61.33%) | 112 (25.63%) | 57 (13.04%) |
| web_1442 | 332 | 1,442 | 1,284 (89.04%) | 93 (6.45%) | 65 (4.51%) |
| web_10000 | 2,202 | 10,000 | 9,892 (98.92%) | 85 (0.85%) | 23 (0.23 %) |

**web_437 and web_1442: some heuristics are applied to balance the class sizes.**
**web_10000 reflects the underlying distribution of the class sizes – very unbalanced.**

# Knowledge Graphs

- Graphical Representation of Human Knowledge
  - Each fact is represented by a triplet **(head entity, relation, tail entity)**




**(Barack Obama,** was born in, **Honolulu)**
**(Barack Obama,** is politician of, **Honolulu)**
**(Barack Obama,** is married to, **Michelle Obama)**
**(Honolulu,** located in, **United States)**
**(Michelle Obama,** lives in, **United States)**
**(Hawaii,** has capital, **Honolulu)**

# Knowledge Graph Embedding

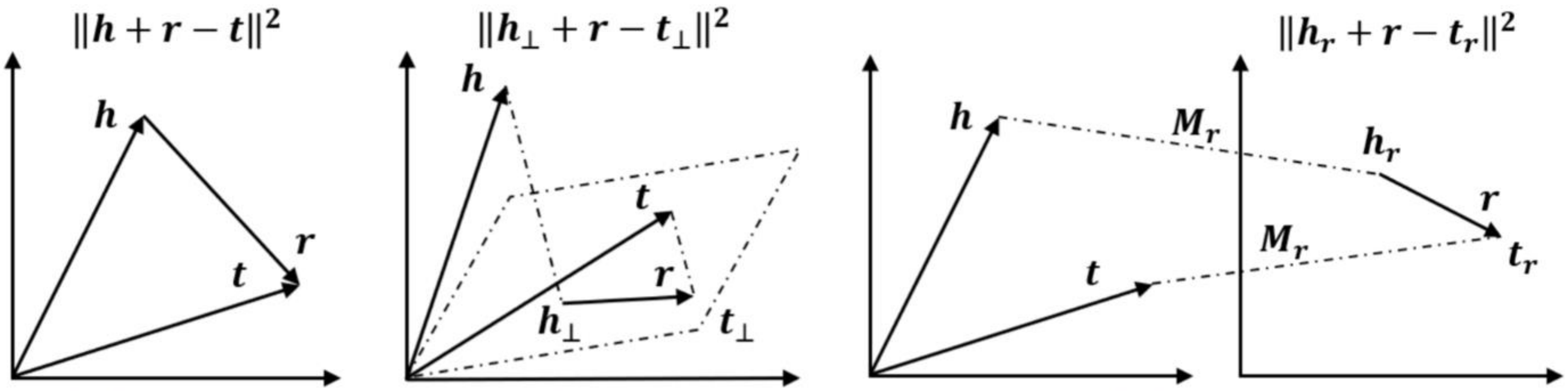
- **Representation Learning Technique**
  - Represents entities and relations in **a feature space**.
  - Given a set of **golden triplets** ($S$) and a set of **corrupted triplets** ($S'$), minimize

$$L = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'} [f(h,r,t) + \gamma - f(h',r,t')]_+$$

**How to compute $f(h,r,t)$ determines different embedding models.**

# Knowledge Graph Embedding

- **Knowledge Graph Embedding Models**
  - **TransE:** Translating Embeddings for Modeling Multi-relational Data
  - **TransH:** Knowledge Graph Embedding by Translating on Hyperplanes
  - **TransR:** Learning Entity and Relation Embeddings for Knowledge Graph Completion

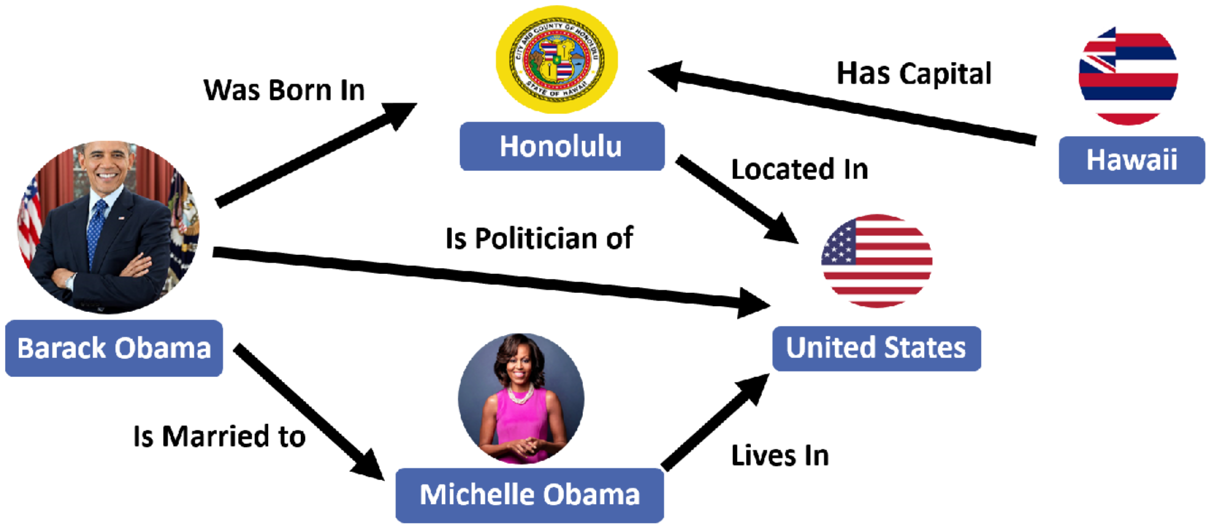



(a) TransE (b) TransH (c) TransR

Image from “Knowledge graph embedding: A survey of approaches and applications.” TKDE 2017.

# Hyperlink Classification Model

- Interpret a **Web Graph** as a **Knowledge Graph**




**(Barack Obama, was born in, Honolulu)**
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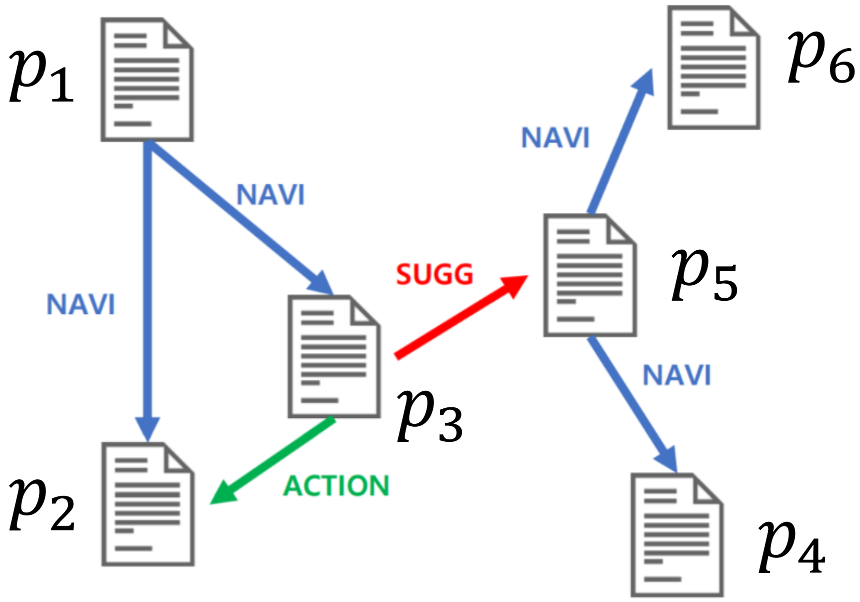
⋮




**( $p_1$, NAVI, $p_3$)**
**( $p_3$, ACTION, $p_2$)**
**( $p_3$, SUGG, $p_5$)**
⋮

# Hyperlink Classification Model

- Model Specification and Training
  - A web graph G = ($\mathcal{V}$, $\mathcal{E}$) where $\mathcal{V}$ = $\{ p_1, p_2, \cdots, p_n\}$, $\mathcal{E}$ = $\{ (p_i, p_j): p_i \in \mathcal{V}, p_j \in \mathcal{V}\}$
  - **Each hyperlink** has one of the three **relation labels $\mathcal{R}$ = {n, s, a}**

$$L = \sum_{(p_i, r, p_j) \in \mathcal{S}} [f(p_i, r, p_j) + \gamma - f(\mathrm{c}(p_i, r, p_j))]_+$$

where $\mathrm{c}(p_i, r, p_j)$ is defined by

$$\mathrm{c}(p_i, r, p_j) = \begin{cases} \text{prob. } \alpha/2: & (p_i, r, q), q \in \mathcal{V} \backslash \{p_j\}, (p_i, r, q) \notin \mathcal{S} \\ \text{prob. } \alpha/2: & (q, r, p_j), q \in \mathcal{V} \backslash \{p_i\}, (q, r, p_j) \notin \mathcal{S} \\ \text{prob. } (1-\alpha): & (p_i, r', p_j), r' \in \mathcal{R} \backslash \{r\} \end{cases}$$

**$\alpha$ controls the chance to corrupt entities ($0 < \alpha \leq 1$)**

# Hyperlink Classification Model

- **Prediction**
  - For a directed edge $(p_i, p_j)$ in a test set, the **relation label** is predicted by

$$r^* = \underset{r \in R}{argmin}\ f(p_i, r, p_j)$$

  - For TransH embedding model, $f(p_i, r, p_j)$ is computed by

$$f(p_i, r, p_j) = \|(\mathbf{p}_i - \mathbf{w}_r{}^T \mathbf{p}_i \mathbf{w}_r) + \mathbf{r} - (\mathbf{p}_j - \mathbf{w}_r{}^T \mathbf{p}_j \mathbf{w}_r)\|_2^2$$

**$p_i$ and $p_j$ : embedding vectors of the pages**

**$r$ : embedding vector for the relation**

**$w_r$ : norm vector of the relation-specific hyperplane**

# Experimental Results

- F1 scores (%) of our model with different α values and the original TransE, TransH, and TransR.

| | | TransE | TransH | TransR |
|---|---|---|---|---|
| web_437 | Our model, $\alpha = 0.3$ | 34.29 | **60.25** | 57.99 |
| | Our model, $\alpha = 0.5$ | 34.39 | 58.87 | 57.32 |
| | Our model, $\alpha = 0.7$ | 33.88 | 58.91 | **59.83** |
| | The original model | **36.22** | 54.04 | 53.22 |
| web_1442 | Our model, $\alpha = 0.3$ | 23.39 | 53.42 | **50.04** |
| | Our model, $\alpha = 0.5$ | **24.86** | **55.16** | 46.18 |
| | Our model, $\alpha = 0.7$ | 21.18 | 52.70 | 45.12 |
| | The original model | 20.05 | 29.94 | 10.35 |
| web_10000 | Our model, $\alpha = 0.3$ | **20.68** | **76.00** | **53.86** |
| | Our model, $\alpha = 0.5$ | 17.98 | 74.64 | 46.99 |
| | Our model, $\alpha = 0.7$ | 19.50 | 72.94 | 44.11 |
| | The original model | 15.31 | 25.35 | 2.08 |

**→ Our model significantly outperforms the original knowledge graph embedding methods.**

**→ Creating corrupted triplets by relation perturbation plays a critical role in the hyperlink classification problem.**

# Experimental Results

- F1 score (%) of each class and the average F1 score

| | | *navigation* | *suggestion* | *action* | Average |
|---|---|---|---|---|---|
| web_437 | Random-predict | 59.75 | 25.81 | 11.07 | 32.21 |
| | Rule-based | 60.20 | 20.96 | 0.00 | 27.05 |
| | TransE-original | 55.78 | 31.96 | 20.93 | 36.22 |
| | TransH-original | 70.80 | 52.75 | 38.56 | 54.04 |
| | TransR-original | 67.87 | 52.86 | 38.94 | 53.22 |
| | Our Model | **77.04** | **57.05** | **46.64** | **60.25** |
| web_1442 | Random-predict | 89.13 | 5.18 | 5.65 | 33.32 |
| | Rule-based | 72.98 | 10.20 | 36.67 | 39.95 |
| | TransE-original | 42.54 | 8.57 | 9.05 | 20.05 |
| | TransH-original | 54.80 | 13.57 | 21.45 | 29.94 |
| | TransR-original | 0.00 | 12.97 | 18.09 | 10.35 |
| | Our Model | **93.48** | **22.88** | **49.12** | **55.16** |
| web_10000 | Random-predict | 98.91 | 1.60 | 0.00 | 33.50 |
| | Rule-based | 68.81 | 1.74 | 9.92 | 26.82 |
| | TransE-original | 43.25 | 2.06 | 0.61 | 15.31 |
| | TransH-original | 63.01 | 12.02 | 1.03 | 25.35 |
| | TransR-original | 0.00 | 5.61 | 0.61 | 2.08 |
| | Our Model | **99.66** | **83.22** | **45.12** | **76.00** |

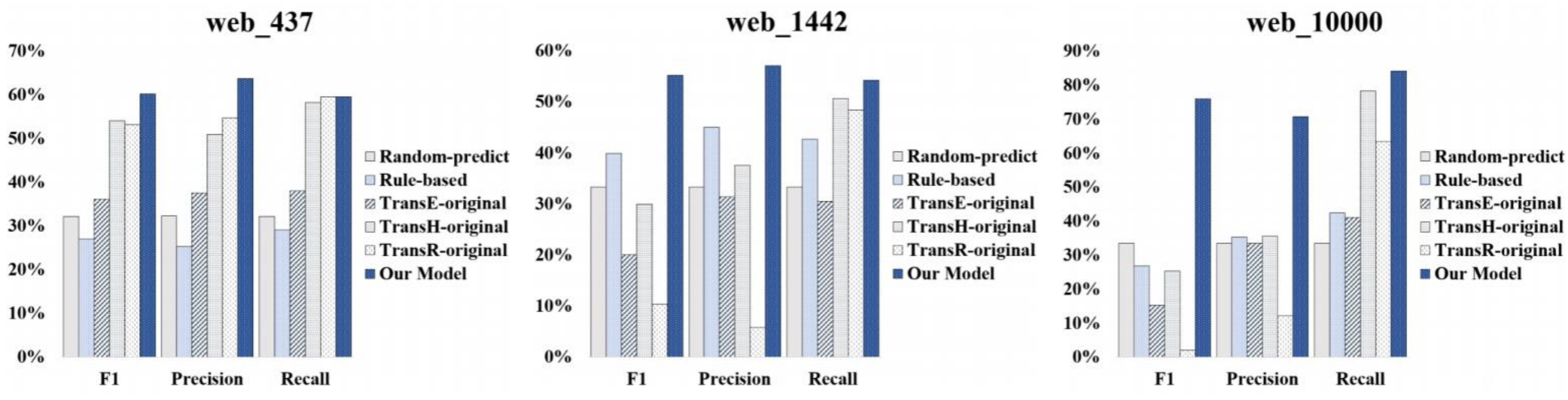
**→ Random-predict: random prediction while preserving the number of hyperlinks in each class.**

**→ Rule-based:**
- **navigation: within-domain hyperlinks**
- **action: ‘edit’, ‘share’, ‘email’, or ‘vote’**
- **suggestion: the rest**

**→ Our model achieves the highest F1 scores.**

# Experimental Results

- The average F1, average precision, and average recall




(a) web_437 (b) web_1442 (c) web_10000

# Experimental Results

- Performance on the original web graphs and the randomly shuffled graphs

| | | *navigation* | *suggestion* | *action* |
|---|---|---|---|---|
| web_437 | Original Graph | 77.04 | 57.05 | 46.64 |
| | Randomly Shuffled Graph | 58.60 | 25.36 | 13.79 |
| web_1442 | Original Graph | 93.48 | 22.88 | 49.12 |
| | Randomly Shuffled Graph | 86.08 | 6.19 | 5.68 |
| web_10000 | Original Graph | 99.66 | 83.22 | 45.12 |
| | Randomly Shuffled Graph | 98.43 | 1.28 | 0.61 |

**Randomly shuffled graph: the relation labels are randomly shuffled.**
**Classification performance significantly degrades on the randomly shuffled graphs.**
**Real-world web graphs have characterized structures in terms of forming each relation type.**
**→ Enables us to predict the relation labels via structured graph embedding.**

# Summary

- **Hyperlink Classification** in Web Search
  - Classify hyperlinks into three classes: **navigation, suggestion, and action**
- Approach the problem from a **structured graph embedding** perspective
  - Interpret a **web graph** as a **knowledge graph**
  - Modify knowledge graph embedding techniques
- **Relation perturbation in negative sampling** enables us to significantly improve performance in classifying hyperlinks on web graphs.

More Information: http://bigdata.cs.skku.edu/