# Temporal Fact Extraction from unstructured text data

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w.r.t finding Country's President Person at Time Task

1) "... The former French president Jacques Chirac, a self-styled affable rogue who was head of state from 1995 to 2007 ..." (posted on Sept. 26, 2019 [text gen. time] ) "
2) "... Emmanuel Macron, now President of France, graduated from ENA in 2004..." (posted on Sept. 19, 2019) "

*--From news data*

Extracted by

Textual Pattern

- Pattern 1: former Country president Person
- Pattern 2: Person, now president of Country

Time Signal :

- temporal tag
- text generate time

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1) "… The former French [Country: France] president Jacques Chirac [Person], a self-styled affable rogue who was head of state from 1995 [temporal tag] to 2007 …" (posted on Sept. 26, 2019 [text gen. time] ) "

2) "… Emmanuel Macron [Person], now President of France [Country], graduated from ENA in 2004 [temporal tag] …" (posted on Sept. 19, 2019 [text gen. time]) "

*--From news data*

Textual Pattern

Pattern 1: former Country president Person

Pattern 2: Person, now president of Country

Time Signal :

- temporal tag
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**Temporal Fact Extraction** ←

- ✔ (France, Jacques Chirac, 1995): **P1** and **temporal tag**;
- ✗ (France, Jacques Chirac, 2019): **P1** and **text gen.time**;
- ✗ (France, Emmanuel Macron, 2004): **P2** and **temporal tag**;
- ✔(France,EmmanuelMacron,2019):**P2** and **textgen.time**.

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## Here, we have some observations about Temporal Fact Extraction:

**O1: Not every pattern is reliable, Patterns have reliability .**

pattern such as *"Person visited Country"* is very likely to be unreliable; and pattern such as *"current Country's president Person"* is very likely to be reliable.

**O2: There is a dependency between pattern and type of time signal**

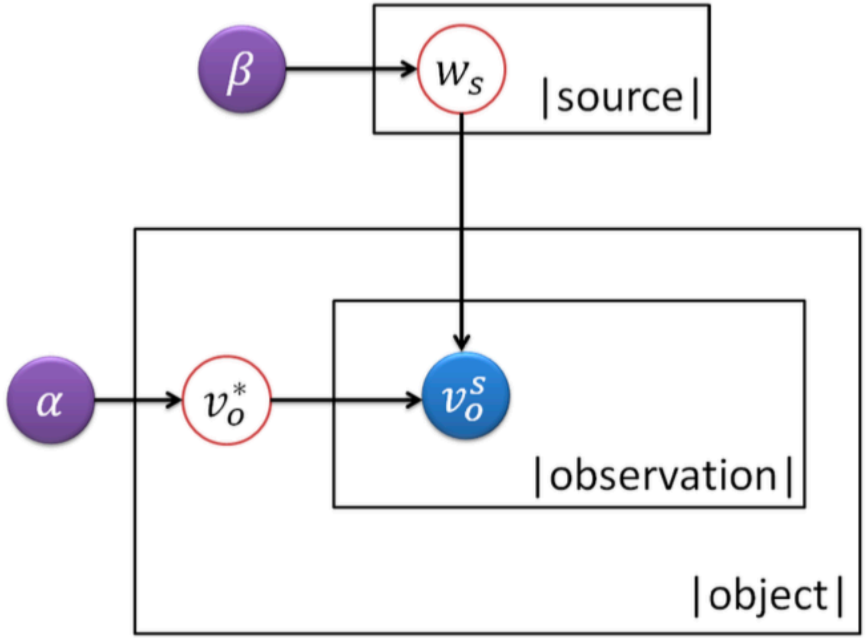
For temporal fact extraction, different types of time signals might be either reliable or unreliable depending on the pattern.

# Truth Discovery via PGM

Truth discovery approaches follow two fundamental principles:

(1) If a source provides much trustworthy information, its reliability is high

(2) If an Information is supported by many reliable source, this information is more likely to be true.




**How to design a PGM for temporal truth discovery?**

# Temporal Truth: Commonsense constraint

Here, we have some commonsense constraint about Temporal Truth:

**For country's president:**

- one president serves only one country;
- one country has only one president at a time;
- one country can have multiple presidents in the history (e.g., United States, France).

**For sports team's player:**

- one player serves only one club at a time;
- one club has multiple players and one player can serve multiple clubs in his/her career.

**generalize**

- C1: one value matches with only one entity;
- C2: one entity matches with only one value;
- C3: one value matches with only one entity at a time;
- C4: one entity matches with only one value at a time.

# Temporal Truth: Commonsense constraint

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## Commonsense Constraint Rules

- C1: one value matches with only one entity;
- C2: one entity matches with only one value;
- C3: one value matches with only one entity at a time;
- C4: one entity matches with only one value at a time.

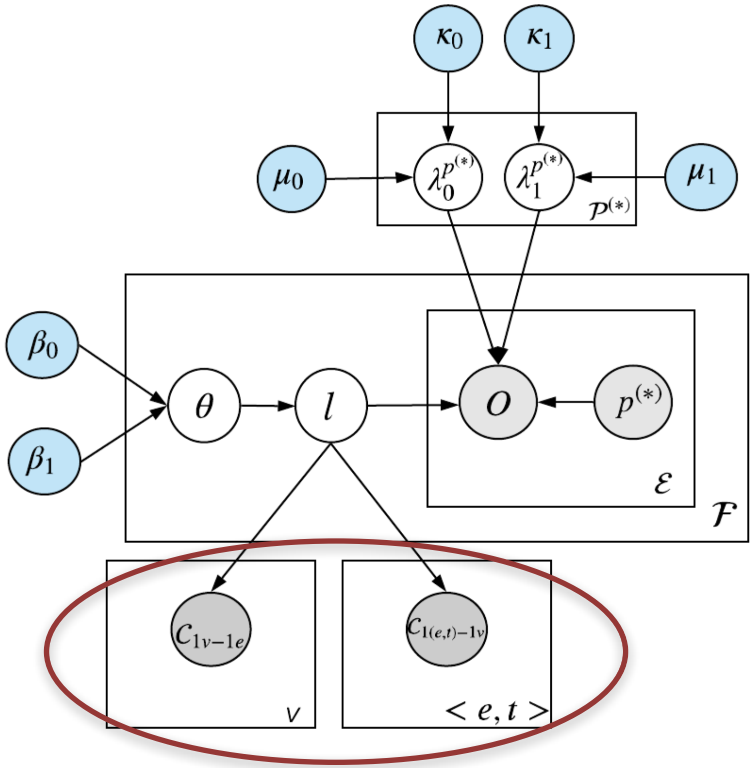
However, In probabilistic graphic model, all the nodes are variable

**How to add Commonsense Constraint Rules to PGMs ?**

?

# PGMCC:

## Probabilistic Graphic Model with Commonsense Constraint




Constraint variable

| Symbol | Description |
|---|---|
| $\theta_f$ | [0, 1], trustworthiness of temporal fact tuple $f$ |
| $l_f$ | Boolean: label of temporal fact $f$ |
| $o_e$ | Integer: the observed frequency of fact $f_e$ extracted by pattern $p_e^{(*)}$ |
| $\lambda_0^{p^{(*)}}, \lambda_1^{p^{(*)}}$ | Real numbers: reliability of pattern $p^{(*)}$ on giving false/true fact tuples |
| $C_{1v-1e}$ | Real number: the number of entities given one value $v$ |
| $C_{1(e,t)-1v}$ | Real number: the sum of values given one entity $e$ and one time $t$ |
| **Hyper-Parameter** | |
| $\mu_0, \mu_1$ | Integers: prior counts of false/true tuples extracted by a textual pattern |
| $\kappa_0, \kappa_1$ | Integers: prior sums of false/true tuples extracted by a textual pattern |
| $\beta_0, \beta_1$ | Integers: prior counts of false/true tuples |

**Table 2: Symbols and their descriptions used in the model.**

# PGMCC: Experiment

Take a **MCMC** method to inference it.

**Dataset:**

- 9,876,086 news articles (4 billion words) published from 1994– 2010.
- focus on attribute country's president.
- 57,472 textual patterns, 116,631 temporal fact tuples, and 1,326,164 extractions.

**Experiment Result:**

- Compare with Truth discovery model(without constraint) **LTM**, PGMCC improve the AUC and F1 by **40%+.**
- Compare with Truth finding method **TFWIN** (a bootstrap method not PGMs), PGMCC improve the AUC and F1 by 7**%+.**

# PGMCC: case study

| Method | Entity e | Value v | Year t |
|---|---|---|---|
| PGMCC $C_{1(e,t)-1v}$ | France | j.r_chirac | 1995 |
| | France | j.r_chirac | 1996 |
| | France | j.r_chirac | 1997 |
| | France | j.r_chirac | 1998 |
| | France | **j.r_chirac** (**n.s_sarkozy**) | 1993 |
| | **Spain** (**France**) | j.r_chirac | 1996 |
| | **Greece** (**France**) | j.r_chirac | 2003 |
| | **Tunisia** (**France**) | j.r_chirac | 2003 |
| PGMCC $C_{1(e,t)-1v}$, $C_{1v-1e}$ | France | j.r_chirac | 1995 |
| | France | j.r_chirac | 1996 |
| | France | j.r_chirac | 1999 |
| | France | j.r_chirac | 1997 |
| | France | j.r_chirac | 1998 |
| | Spain | l._enrique | 1996 |
| | Greece | **c._photopoulos** (**k_stephanopoulos**) | 2003 |
| | Tunisia | a._ben_ali | 2003 |

**Table 4: False case analysis for comparing PGMCC of partial and complete commonsense constraints.**

- **C1(e,t)-1v** → one country one year has only one president
- **C1v-1e** → one President only serve one Country

- **Red** means false, **Green** means right answer