Stacked Ensembles of Information Extractors for Knowledge-Base Population

Raymond J. Mooney
Nazneen Rajani, Vidhoon Vishwanathan, Yinon Bentor
University of Texas at Austin

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Microsoft

THE UNIVERSITY OF TEXAS AT AUSTIN

Knowledge-Base Population
(KBP)

- Annual evaluation of relation extraction from natural language documents organized by NIST.
- English Slot Filling (ESF) task:

per: Barack Obama
country_of_birth United States
spouse Michelle Obama
children Malia Obama Sasha Obama

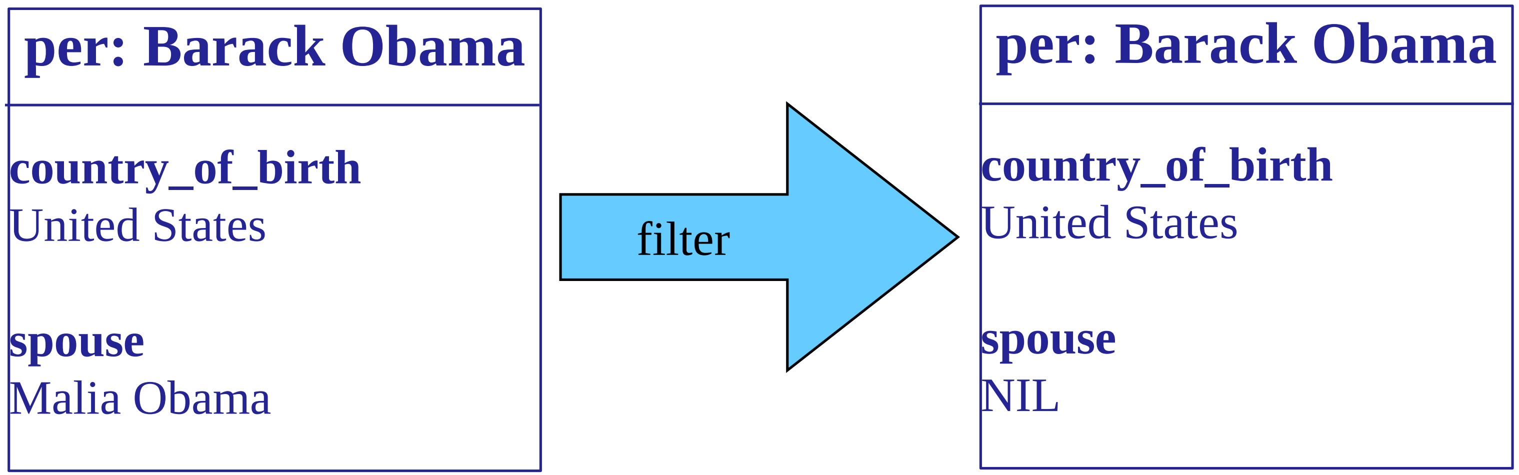
org: Microsoft
city_of_headquarters Redmond
website microsoft.com
subsidiaries Skype Nokia

KBP Provenance

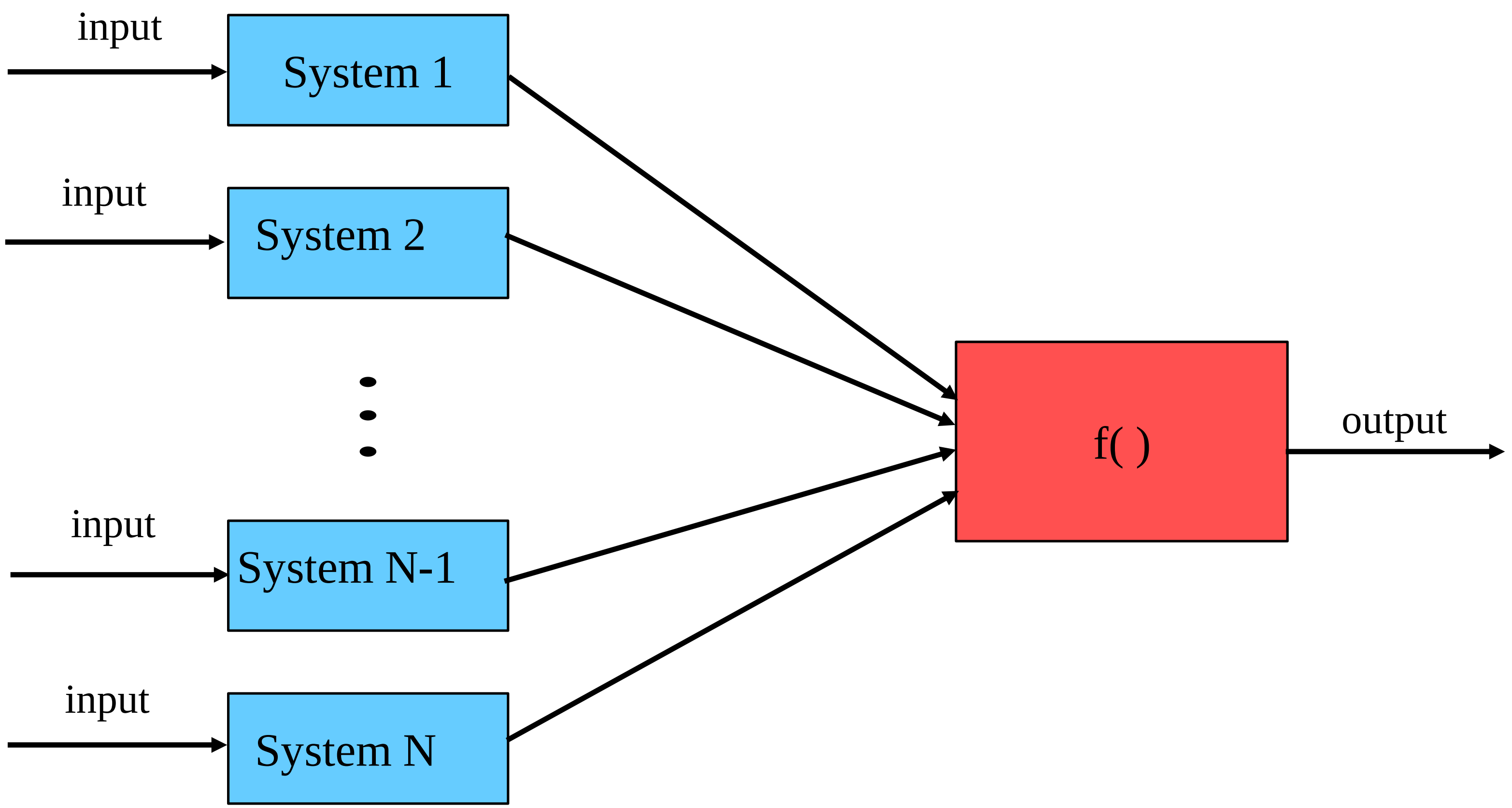
- System's must provide information on where the evidence for each slot fill is in the document corpus.
- Given by:
  - Doc ID
  - Start Offset
  - End Offset

org: Microsoft
<eng-NG-31-1007>: Microsoft is a technology company headquartered in Redmond, Washington, that develops …
city_of_headquarters Redmond **Doc ID** eng-NG-31-1007 **Start Offset** 48 **End Offset** 54

- Aim: Improve precision of individual systems.
- Input is system outputs from the ESF task.
- Output is filtered slot fills.
- Ensembling used to improve recall as well.



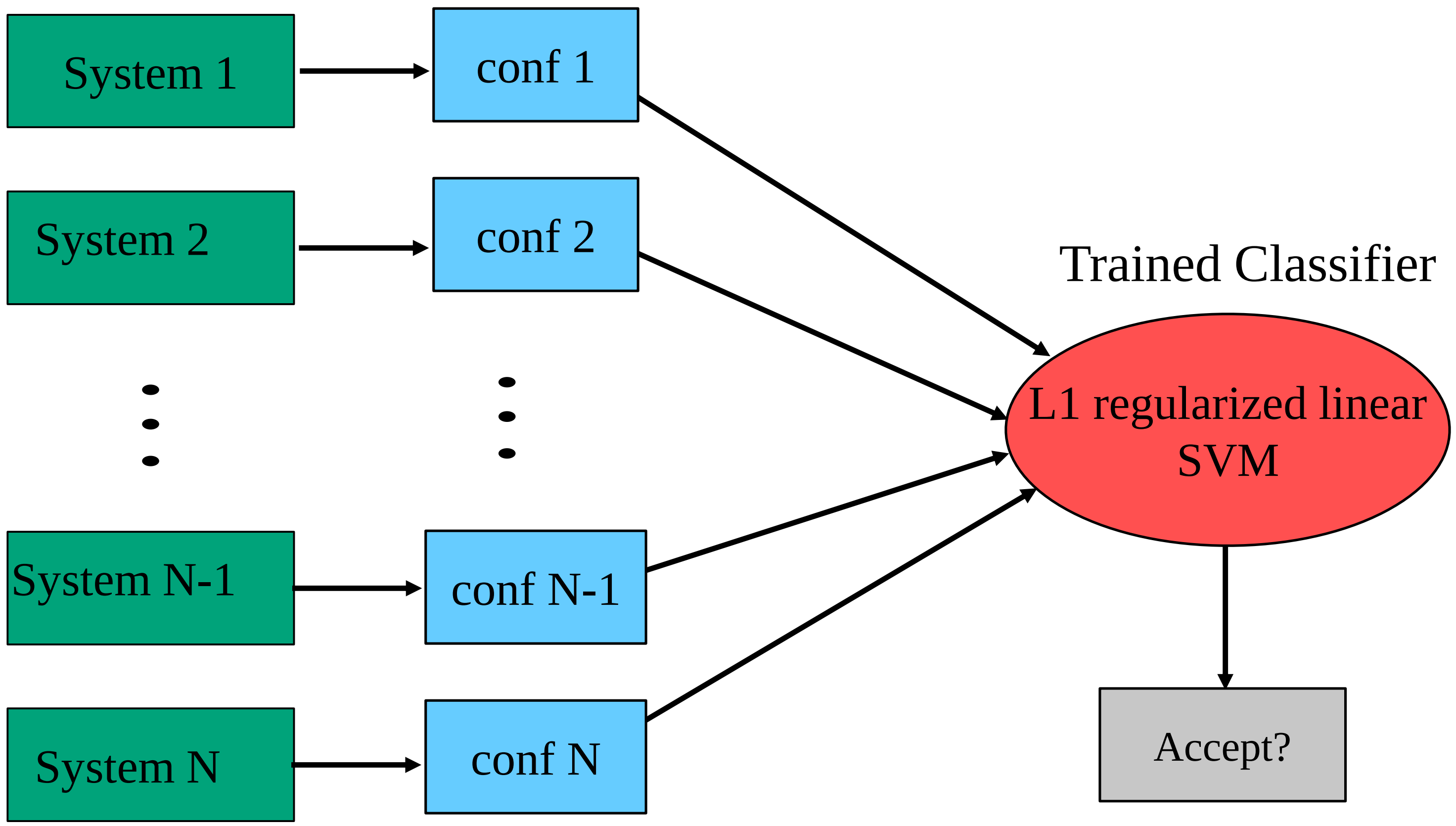
Ensembling



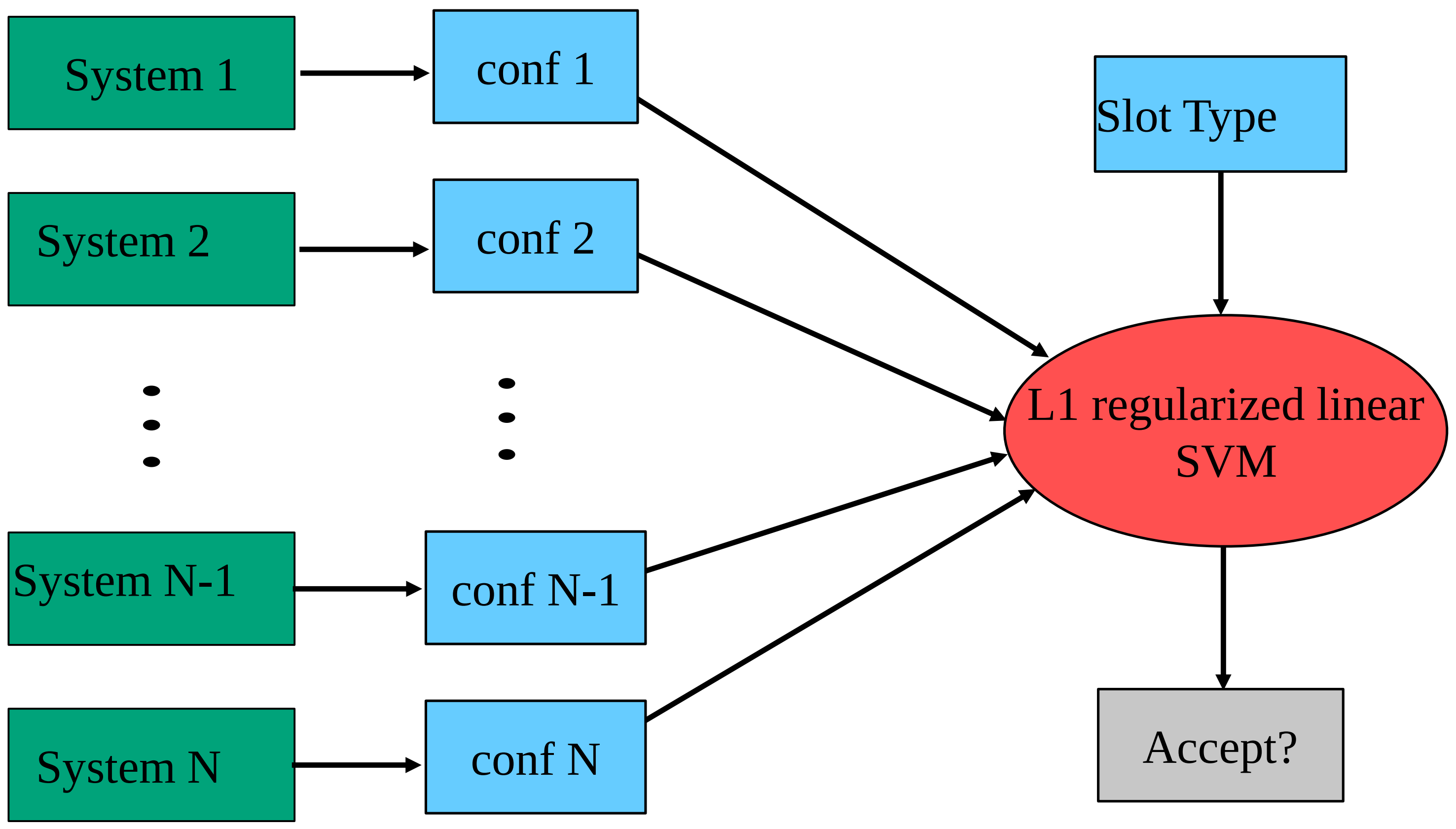
input
System 1
input
System 2
input
System N-1
input
System N
f( )
output

Stacking
(Wolpert, 1992)

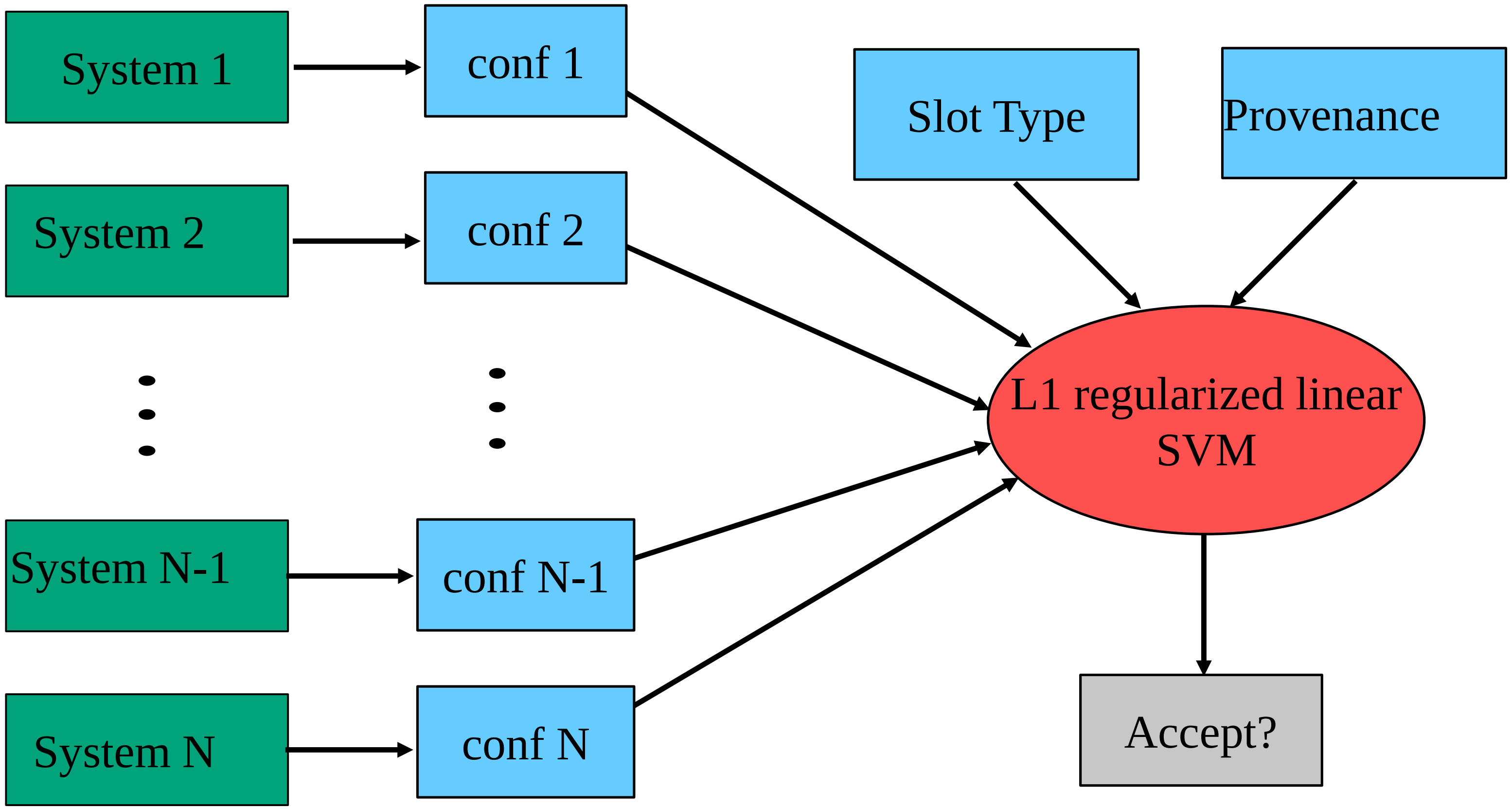
For a given proposed slot-fill, e.g. `spouse(Barak, Michelle)`, combine confidences from multiple systems:



Stacking with Features



Stacking with Features



Document Provenance Features

- For a given query and slot, for each system, *i*, there is a feature DP_i:
  - N systems provide a fill for the slot.
  - Of these, n give same provenance *docid*.
  - $DP_i = n/N$ is the document provenance score.
- Measures extent to which systems agree on document provenance of the slot fill.

Offset Provenance Features

- Degree of overlap between systems' provenance strings (prov).
- Uses Jaccard similarity coefficient.
- For a given query and slot, for each system, *i*, there is a feature OP_i :
  - *N* systems provide a fill with same *docid*
  - Offset provenance for a system *i* is calculated as:

$$OP_i = \frac{1}{|N|} \times \sum_{j \in N, j \neq i} \frac{|\mathrm{prov}(i) \cap \mathrm{prov}(j)|}{|\mathrm{prov}(i) \cup \mathrm{prov}(j)|}$$

  - Systems with different *docid* have zero OP

Datasets

- Ten Common Systems that participated both in 2013 and 2014:
  - LSV
  - IIRG
  - UMASS_IESL
  - Stanford
  - BUPT_PRIS
  - RPI_BLENDER
  - CMUML
  - NYU
  - Compreno
  - UWashington
- 2014 Slot Filler Validation data
  - 17 teams
  - 65 systems

Baselines

- Union
  - Combine systems for maximizing recall
  - List valued slot fills => always included
  - Single valued slot fills => highest confidence
- Voting
  - Combine systems for maximizing precision
  - Vary threshold on #systems that must agree
  - Learn threshold on 2013 data
  - SFV and common systems datasets

KBP English Slot Filling Results

2014 Slot Filler Validation (SFV) Data

Baseline	Precision	Recall	F1
Union	0.067	**0.762**	0.122
Voting	**0.641**	0.288	**0.397**

Common systems for 2013 and 2014 ESF task

Approach	Precision	Recall	F1
Union	0.176	**0.647**	0.277
Voting	**0.694**	0.256	0.374
Best ESF system in 2014 (Stanford)	0.585	0.298	0.395
Stacking	0.606	0.402	0.483
Stacking + Relation	0.607	0.406	0.486
Stacking + Provenance + Relation	0.541	0.466	**0.501**

KBP Slot Filler Validation Results

2014 Slot Filler Validation (SFV) Data

Baseline	Precision	Recall	F1
Union	0.054	**0.877**	0.101
Voting	**0.637**	0.406	**0.496**

Common systems for 2013 and 2014 ESF task

Approach	Precision	Recall	F1
Union	0.177	**0.922**	0.296
Voting	**0.694**	0.256	0.374
Best SFV system in 2014 (UIUC)	0.457	0.507	0.481
Stacking	0.613	0.562	0.586
Stacking + Relation	0.613	0.567	0.589
Stacking + Provenance + Relation	0.659	0.56	**0.606**

Conclusion

- Stacked meta-classifier beats the best performing 2014 KBP ESF system by an F1 gain of **11** points.
- Features that utilize provenance information improve stacking performance.
- Ensembling has clear advantages but naive approaches such as voting do not perform as well.