

# Fonduer: Knowledge Base Construction from Richly Formatted Data

**Sen Wu**

Stanford University



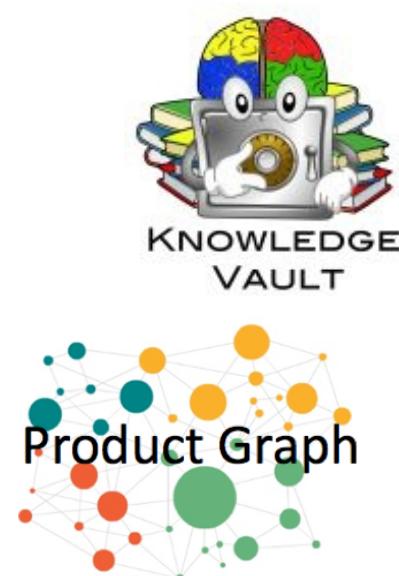
# Knowledge bases are everywhere...



Unstructured Information



Knowledge Base Construction



Structured Knowledge Base



And many more...

But, troves of "richly formatted" information remains untapped

# Richly formatted data

**Richly formatted data:** information is expressed via textual, structural, tabular, and visual cues.



## Transistor Datasheet (PDF)

SMBT3904...MMBT3904

### NPN Silicon Switching Transistors

- High DC current gain: 0.1 mA to 100 mA
- Low collector-emitter saturation voltage

### Maximum Ratings

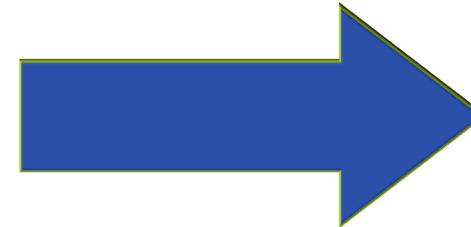
Parameter	Symbol	Value	Unit
Collector-emitter voltage	$V_{CEO}$	40	V
Collector-base voltage	$V_{CBO}$	60	
Emitter-base voltage	$V_{EBO}$	6	
Collector current	$I_C$	200	mA
Total power dissipation $T_S \leq 71^\circ\text{C}$	$P_{tot}$	330	mV
$T_S \leq 115^\circ\text{C}$		250	
Junction temperature	$T_j$	150	$^\circ\text{C}$
Storage temperature	$T_{stg}$	-65 ... 150	

# Knowledge base construction from richly formatted data

**Goal: extract maximum collector current from transistor datasheets**

## Transistor Datasheet

SMBT3904..MMBT3904			
NPN Silicon Switching Transistors			
Maximum Ratings			
Parameter	Symbol	Value	Unit
Collector-emitter voltage	$V_{CEO}$	40	V
Collector-base voltage	$V_{CBO}$	60	
Emitter-base voltage	$V_{EBO}$	6	
Collector current	$I_C$	200	mA
Total power dissipation $T_S \leq 71^\circ\text{C}$	$P_{\text{tot}}$	330	mV
$T_S \leq 115^\circ\text{C}$		250	
Junction temperature	$T_j$	150	°C
Storage temperature	$T_{\text{stg}}$	-65 ... 150	



HasCollectorCurrent	
Transistor Part	Current
SMBT3904	200mA
MMBT3904	200mA

Knowledge Base

# Knowledge base construction from richly formatted data

## Transistor Datasheet

Font: Arial, Size: 9pt, Style: Header: SMBT3904..MMBT3904

NPN Silicon Switching Transistors				
• High DC current gain: 0.1 mA to 100 mA				
• Low collector-emitter saturation voltage				
<b>Maximum Ratings</b>				
<b>Table</b>				
Parameter	Symbol	Value	Unit	Value
Collector-emitter voltage	$V_{CEO}$	40	mA	40
Collector-base voltage	$V_{CBO}$	60	mA	60
Emitter-base voltage	$V_{EBO}$	6	mA	6
Collector current	$I_C$	200	mA	200
Total power dissipation	$P_{tot}$	NER:	mV	mV
$T_S \leq 71^\circ C$	330	Numbers	330	
$T_S \leq 115^\circ C$	250		250	
Junction temperature	$T_J$	150	$^\circ C$	150
Storage temperature	$T_{stg}$	-65...150		

In richly formatted data, semantics are expressed in **textual**, **structural**, **tabular**, and **visual** modalities throughout a document

**Conventional approach 1:** Filter out other modalities besides unstructured text

**Conventional approach 2:** Limit the context scope to sentences or tables.

**Problem:** Misses important relations if you neglect multimodal information

Up to 97%  
missed relations!

# Deep learning is very successful in many domains



Andrej Karpathy [Follow](#)

Director of AI at Tesla. Previously Research Scientist at OpenAI and PhD student at Stanford. I like to train deep neural nets on large datasets.

Nov 11, 2017 · 8 min read

## Software 2.0

I sometimes see people refer to neural networks as just “another” tool in your machine learning work here or there, and sometimes. Unfortunately, Neural networks are a fundamental part of a fundamen

### Alibaba's artificial intelligence bot beats humans at reading in a first for machines

A deep neural network model developed by Alibaba has scored higher than humans in a reading comprehension test, paving the way for bots to replace people in customer service jobs

PUBLISHED : Monday, 15 January, 2018, 11:33am  
UPDATED : Monday, 15 January, 2018, 12:17pm



**SQuAD**  
The Stanford Question Answering Dataset

tool in your work here or ons.

### H2O Deep Learning beats MNIST

```
> install.packages("h2o")
> library(h2o)
> h2oServer <- h2o.init(ip="mr-0xd1", port=53322)
> train_hex <- h2o.importfile(h2oServer, "mnist/train.csv.gz")
> test_hex <- h2o.importfile(h2oServer, "mnist/test.csv.gz")
> record_model <- h2o.deeplearning(x = 1:784, y = 785, data = train_hex,
activation = "RectifierWithDropout", epochs = 8000, l1 = 1e-5, input_dropout_ratio = 0.1)
```

Actual	0	1	2	3	4	5	6	7	8	9	Error
0	974	1	1	0	0	2	1	1	0	0.00612	
1	0	1135	0	1	0	0	0	0	0	0.00088	
2	0	0	1028	0	1	0	0	3	0	0.00388	
3	0	0	0	1003	0	0	0	3	2	1.00693	
4	0	0	1	0	971	0	4	0	0	0.01120	
5	2	0	0	5	0	882	1	1	1	0.01121	
6	2	3	0	1	1	2.949	0	0	0	0.00939	
7	1	2	6	0	0	0	0	1019	0	0.00875	
8	1	0	1	3	0	4	0	0	2.960	3.01437	
9	1	2	0	0	4	3	0	2	0	0.01189	

## KEY MOMENTS IN DEEP-LEARNING HISTORY 2014-2016

**2014 JANUARY**  
Google acquires DeepMind, a startup specializing in combining deep learning and reinforcement learning, for \$600 million.

**2015 DECEMBER**  
A team from Microsoft, using neural nets, outperforms a human on the ImageNet challenge.

**2016 MARCH**  
DeepMind's AlphaGo, using deep learning, defeats world champion Lee Sedol in the Chinese game of go, four games to one.



LEE JIN-MAN—AP PHOTO

François Chollet [Follow](#)

It is my impression that the world of deep learning \*research\* is starting to plateau. What's booming: deploying DL to real-world problems.

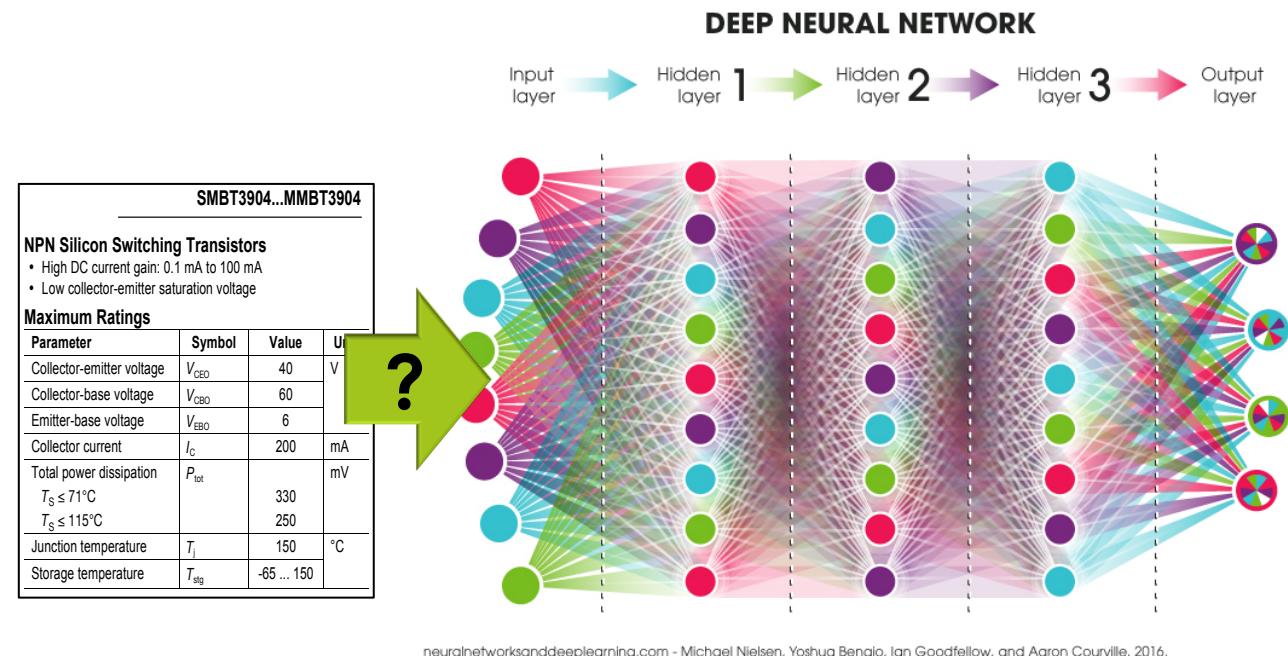
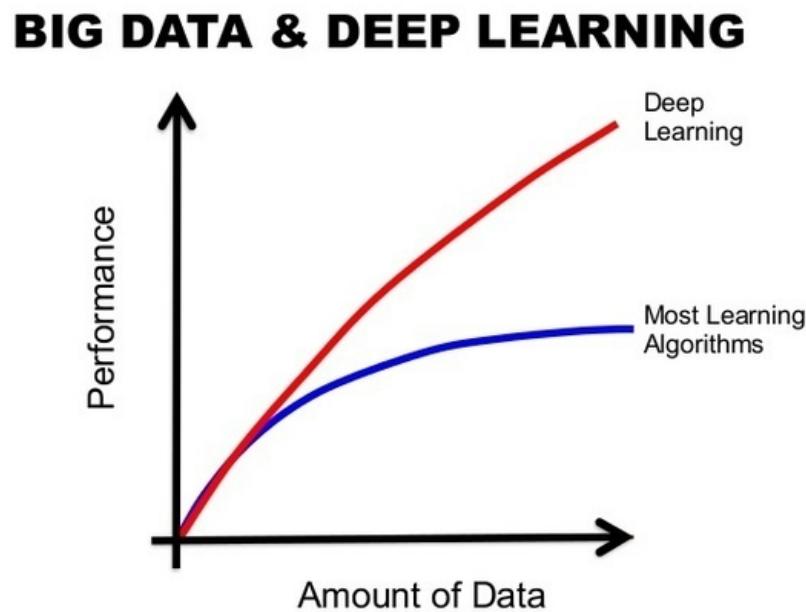
11:19 AM - 9 Sep 2017

186 Retweets 484 Likes

[Reply](#) [Retweet](#) [Like](#) [Email](#)

Can we take advantage of this powerful tool and apply it to our problem?

# Keys to utilizing deep learning



How do we gather enough labeled, richly formatted data?

How do we model the characteristics of richly formatted data in DL?



# Fonduer

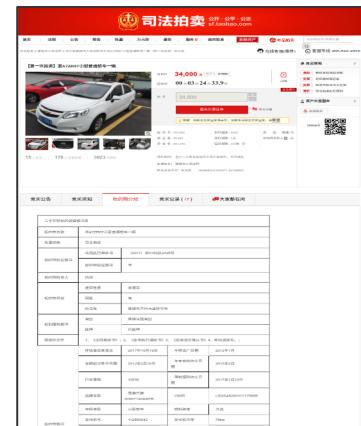
A weakly supervised deep learning framework for  
knowledge base construction from richly formatted data

# FONDUER

# Fonduer in practice!



Anti-Human Trafficking



Search Engine



Genome-wide  
Association Studies

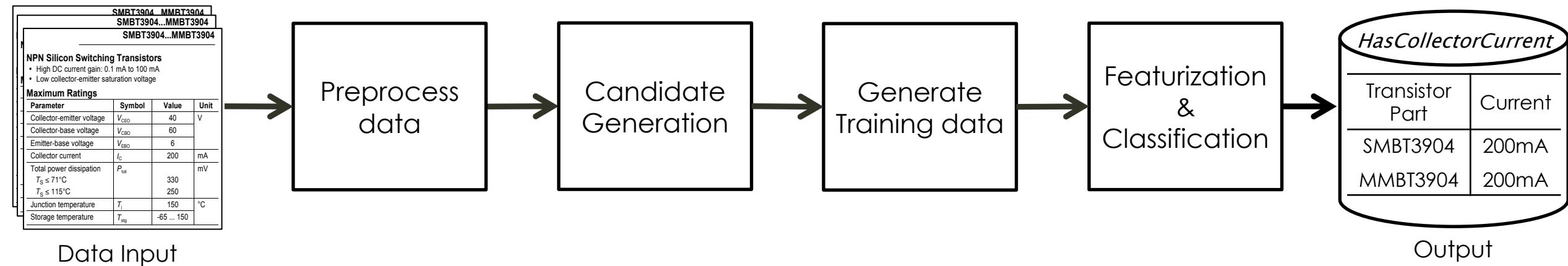


Internet  
of Things



Paleontology

# Fonduer pipeline



# Generating richly formatted training data

# Multimodal weak supervision

**Transistor Datasheet**

SMBT3904..MMBT3904			
NPN Silico	Candidate 1	Transistors	
<ul style="list-style-type: none"> <li>High DC current gain: 0.1 mA to 100 mA</li> <li>Low collector-emitter saturation voltage</li> </ul>			
Maximum Ratings		Candidate 2	
Parameter	Symbol	Value	Unit
Collector-emitter voltage	$V_{CEO}$	40	V
Collector-base voltage	$V_{CBO}$	60	
Emitter-base voltage	$V_{EBO}$	6	
Collector current	$I_C$	200	mA
Total power dissipation $T_S \leq 71^\circ\text{C}$ $T_S \leq 115^\circ\text{C}$	$P_{tot}$	330 250	mV
Junction temperature	$T_j$	150	$^\circ\text{C}$
Storage temperature	$T_{stg}$	-65 ... 150	

Doc. level Candidates	Supervision	
	Manual	Labeling function
SMBT3904	100	✗
MMBT3904	200	✓

**Weak supervision:** express any supervision signal via labeling functions to generate training data

```
# Check if current is in the same row with keyword `collector`
def in_the_same_row_with(candidate):
    if 'collector' in row_ngrams(candidate.current):
        return 1
    else: return -1
```

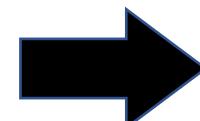
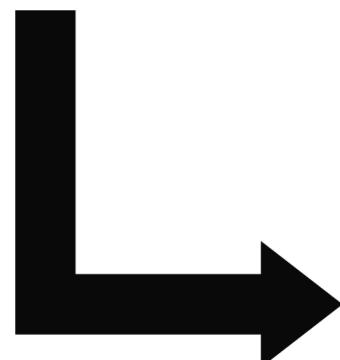
# Modeling Weak Supervision

Doc. level Candidates		Multimodal Supervision		
		Vertically aligned with 'Value'	Row ngrams contain 'mA'	'current' in sentence
SMBT3904	100	✗	∅	✓
SMBT3904	200	✓	✓	✗
SMBT3904	150	✓	✗	✗

∅ = Abstain

**Intuition:** Use agreements / disagreements to learn the accuracy of LFs without ground truth

**Output:** Probabilistic Training Labels



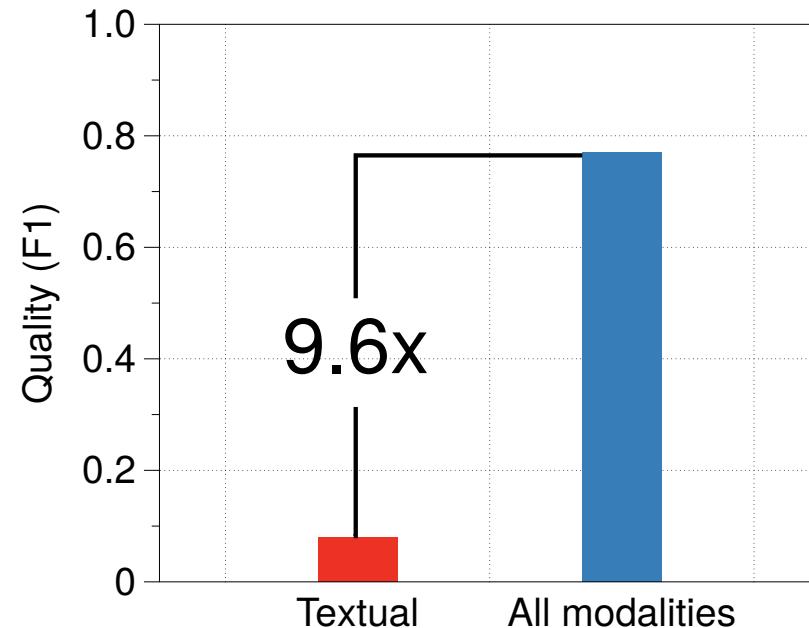
Data programming/MeTal



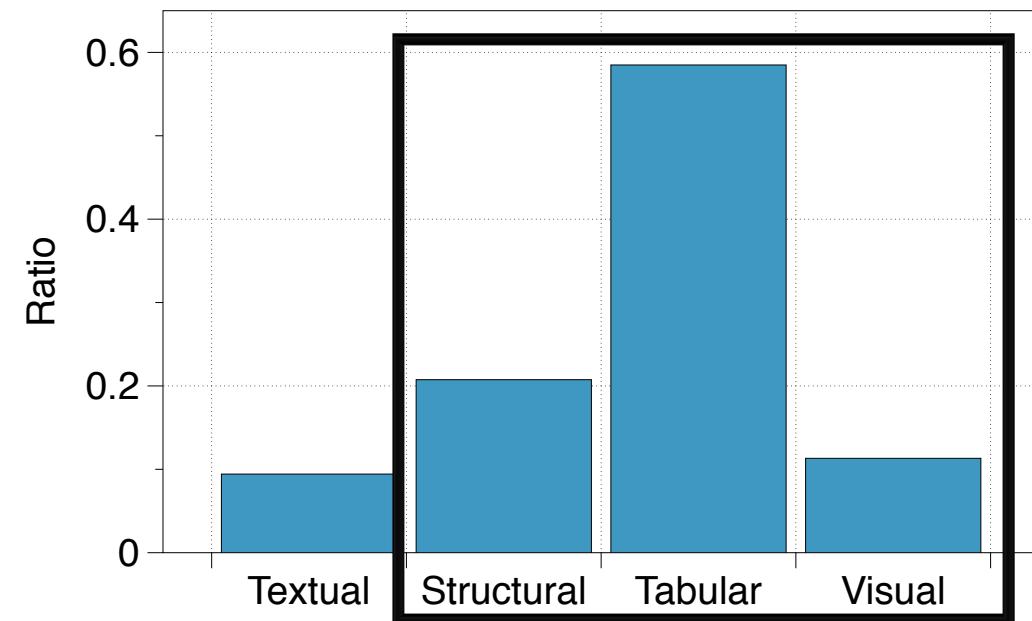
# Multimodal supervision is key to quality

For transistor datasheets...

Different supervision resources' effect



Modality distribution of supervision



**Users intuitively rely on multimodal information for supervision**

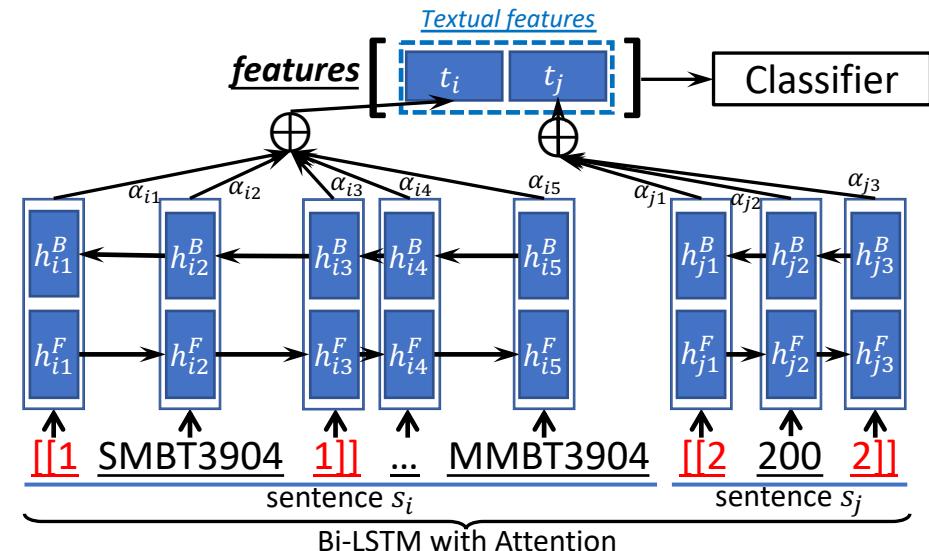
# **Featurization and Classification for Richly Formatted Data**

# LSTM for Textual Information

## Transistor Datasheet

SMBT3904...MMBT3904			
NPN Silicon Switching Transistors			
Parameter	Symbol	Value	Unit
Collector-emitter voltage	$V_{CEO}$	40	V
Collector-base voltage	$V_{CBO}$	60	
Emitter-base voltage	$V_{EBO}$	6	
Collector current	$I_C$	200	mA
Total power dissipation $T_S \leq 71^\circ\text{C}$	$P_{tot}$	330	mV
$T_S \leq 115^\circ\text{C}$		250	
Junction temperature	$T_i$	150	°C
Storage temperature	$T_{stg}$	-65 ... 150	

LSTM excels at relation extraction from text  
Xu et al., 2015; Miwa et al., 2016; Zhang et al., 2016



**Problem:** LSTM networks struggle to capture the multimodal characteristics of richly formatted data.

# Augmenting LSTM with Multimodal Features

## Transistor Datasheet

Font: Arial; Size: 12; Style: Bold {SMBT3904}...MMBT3904

### NPN Silicon Switching Transistors

- High DC current gain: 0.1 mA to 100 mA
- Low collector-emitter saturation voltage

### Maximum Ratings

Parameter	Symbol	Value	Unit
Collector-emitter voltage	$V_{CEO}$	40	V
Collector-base voltage	$V_{CBO}$	30	
Emitter-base voltage	$V_{EBO}$	6	
Collector current	Aligned		200
Total power dissipation $T_S \leq 71^\circ\text{C}$ $T_S \leq 115^\circ\text{C}$	$P_{tot}$	Header: 'Value'; Row: 2; Column: 3 250	°C
Junction temperature	$T_j$	150	
Storage temperature	$T_{stg}$	-65 ... 150	

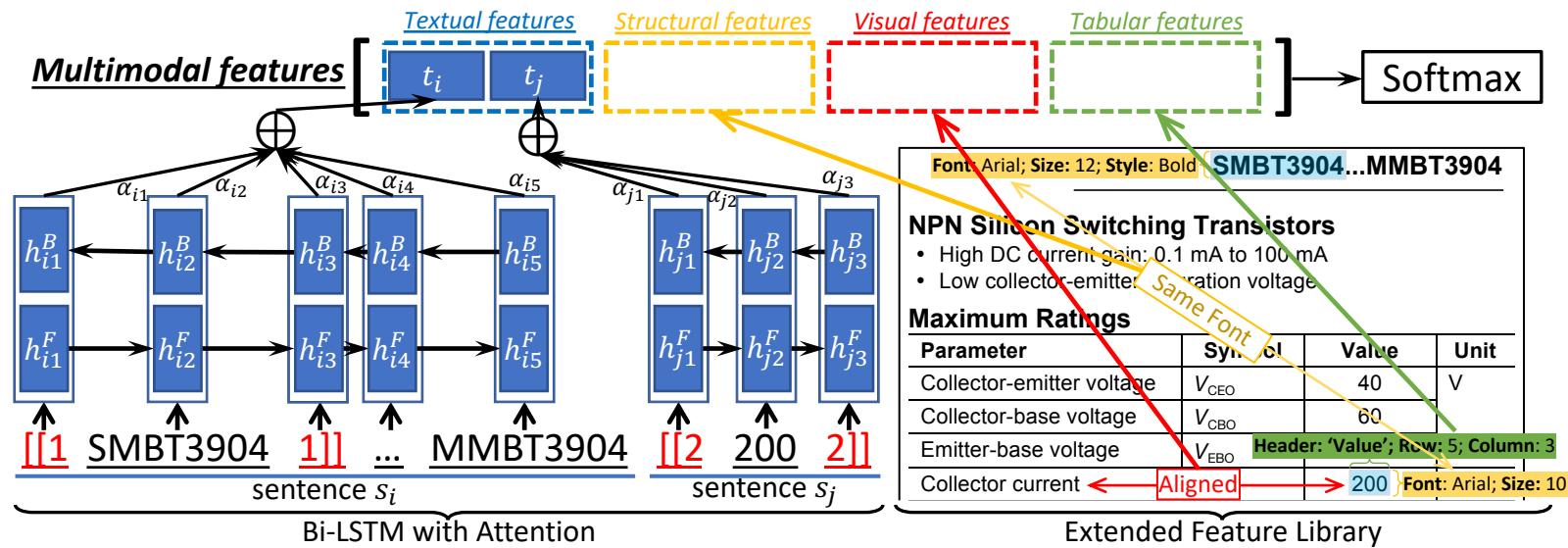
We use the multimodal information stored in the document to extract basic multimodal features:

- Structural features
- Tabular features
- Visual features

**Augmentation with multimodal features captures signals a traditional LSTM would miss.**

# Fonduer's Multimodal LSTM

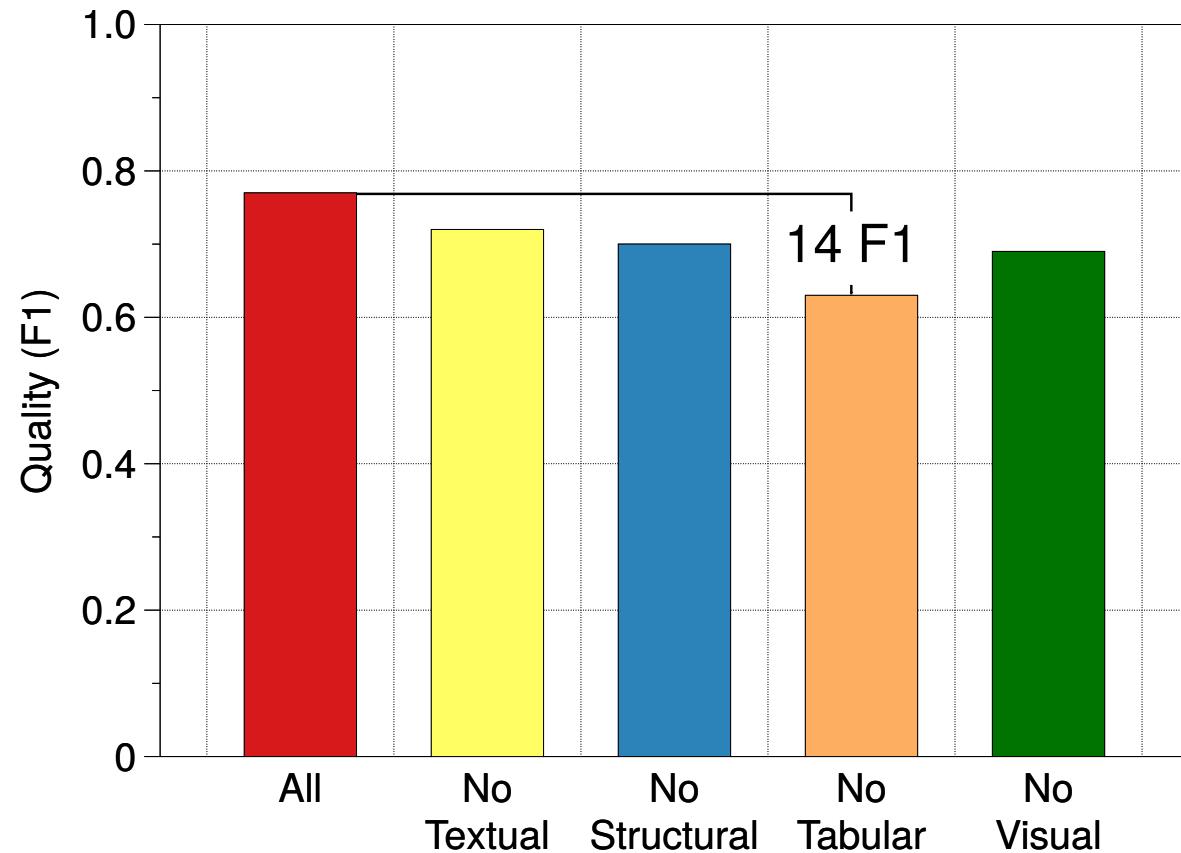
Signals from different modalities can be useful to find the information.



**Fonduer: a KBC system that takes advantage of both techniques to reason about all available signals.**

# The impact of multimodal features

For transistor datasheets...



**Multimodal features significantly impact the quality of extraction**

# Fondue in the wild

Empirical results & real-world uses

# Fonduer vs. Human-curated Knowledge Bases



**Fonduer**

Same set of documents

Human-created

10 years

1.0x extractions

Machine-created

<6 months

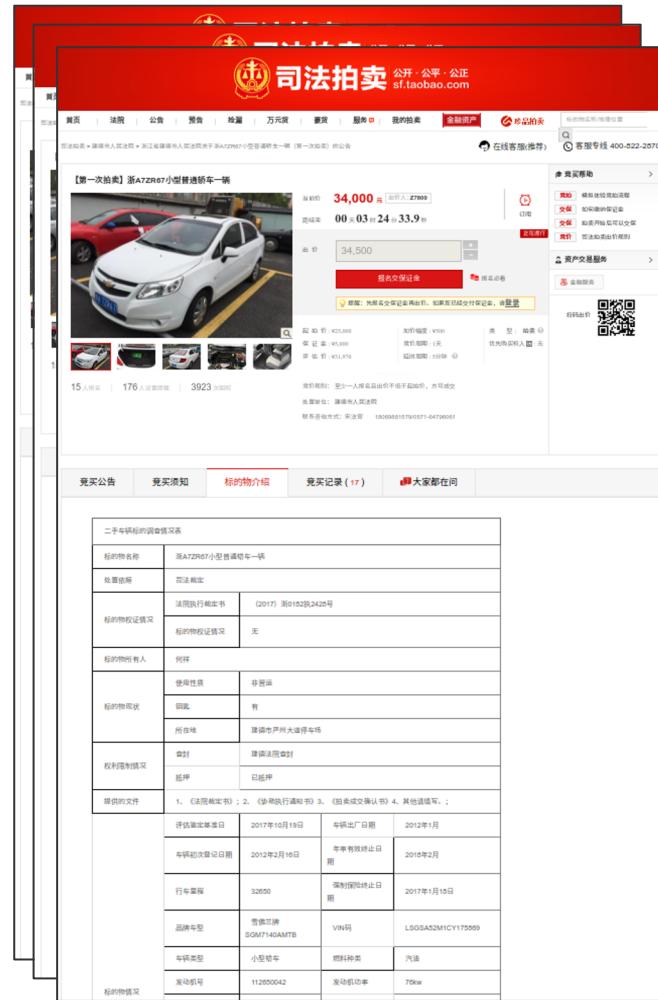
**1.59x** extractions

Precision **0.89**

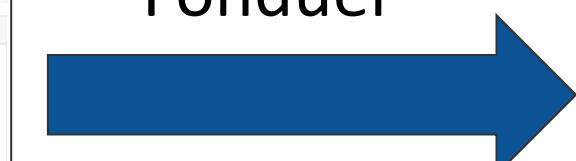
# How people use Fonduer in industry

**Input:** User-customized HTML auction pages → **Output:** Structured knowledge base

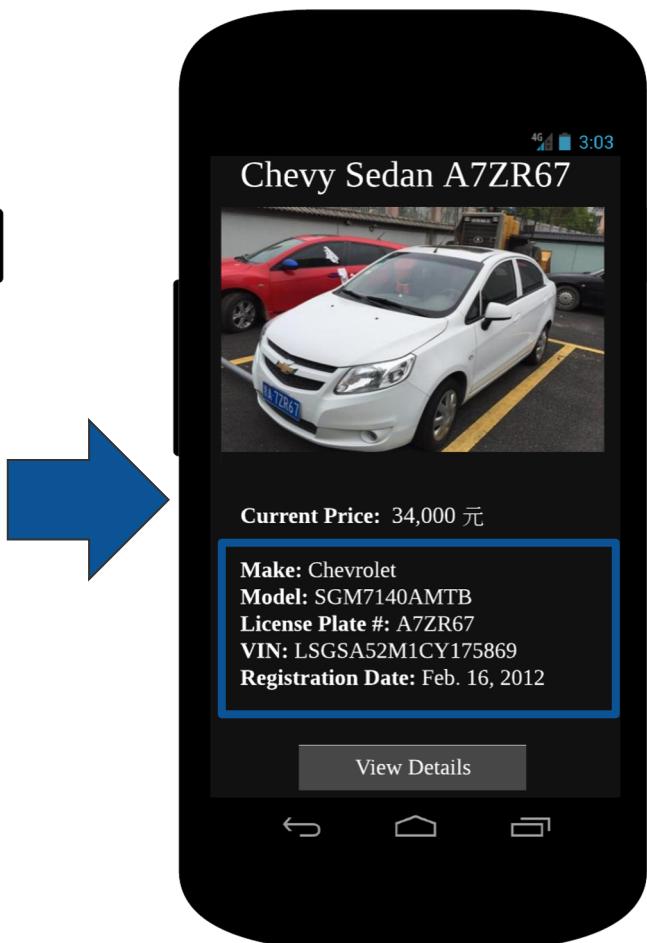
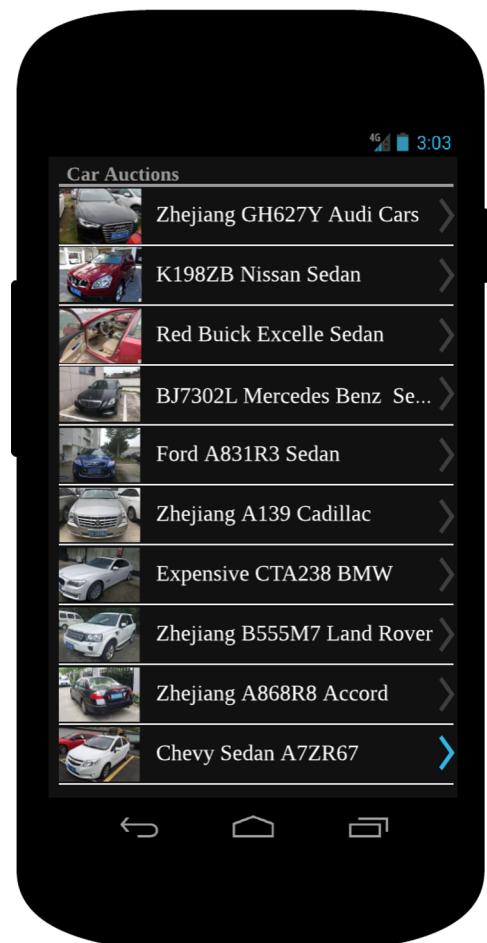
Extract key facts (make, model, license, etc.)



Fonduer



Improve auction search quality and UX



# Knowledge Base Construction from Richly Formatted Data



- Fonduer helps build high-quality KBC from richly formatted data
- Allows users to leverage multimodal signals
- Augments deep learning model with features from each data modality to achieve high quality
- Fonduer is supporting real world applications

Thank you!  
Sen Wu  
[\(senwu@cs.stanford.edu\)](mailto:(senwu@cs.stanford.edu))



**FONDUE**