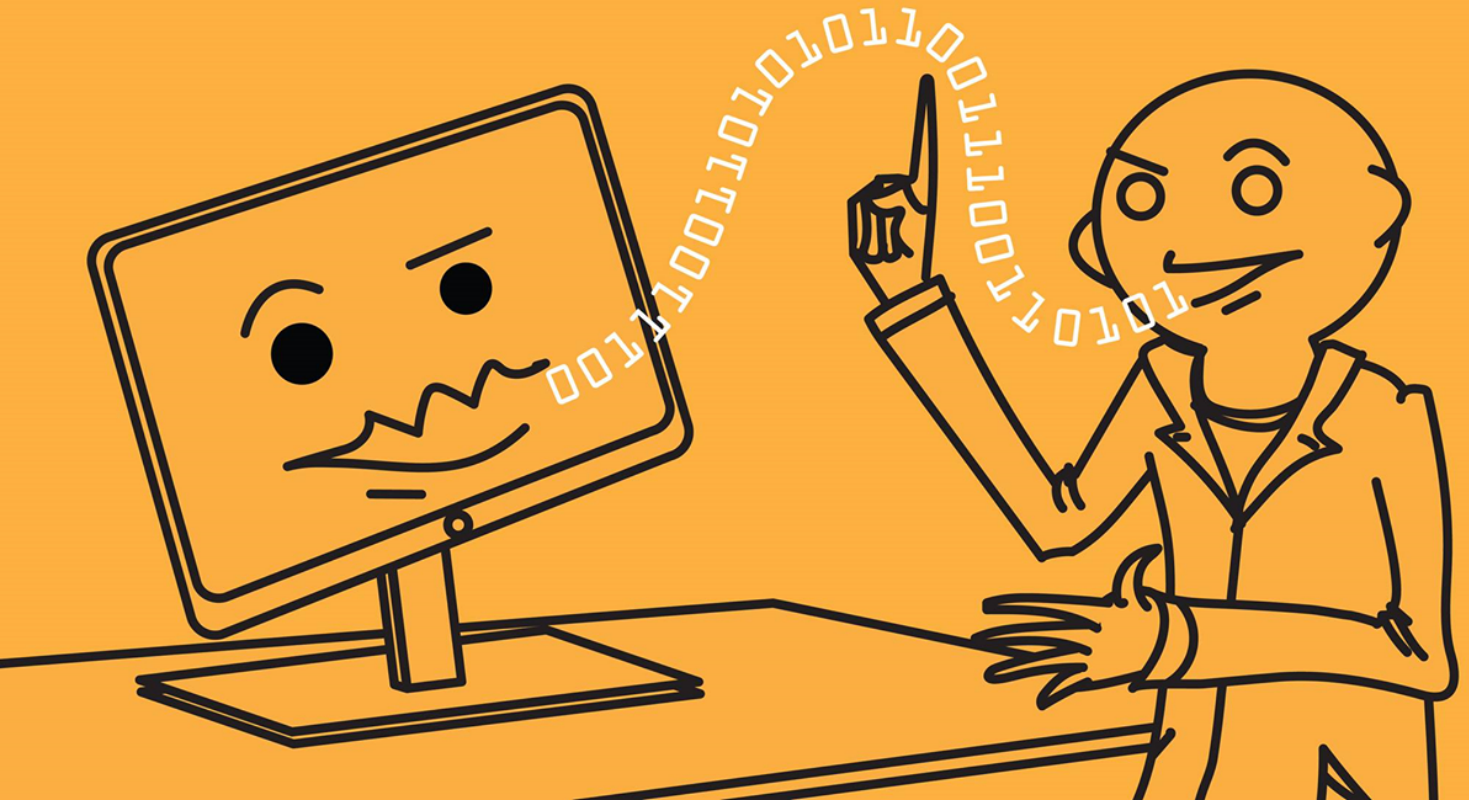
NATURAL LANGUAGE PROCESSING

YURIY GUTS – JUL 09, 2016



NLP MORNING @ LOHIKA

Who Is This Guy?

CIKLUM
EMPOWERING COLLABORATION

Data Science Team Lead

2KNOW
Data Foresight Services

Sr. Data Scientist

eleks®

Software Architect, R&D Engineer

I also teach Machine Learning:

LITS | Lviv IT School

КИЇВСТАР

BIG DATA SCHOOL

What is NLP?

Study of interaction between computers and human languages

NLP = Computer Science + AI + Computational Linguistics

Common NLP Tasks

Easy

- Chunking
- Part-of-Speech Tagging
- Named Entity Recognition
- Spam Detection
- Thesaurus

Medium

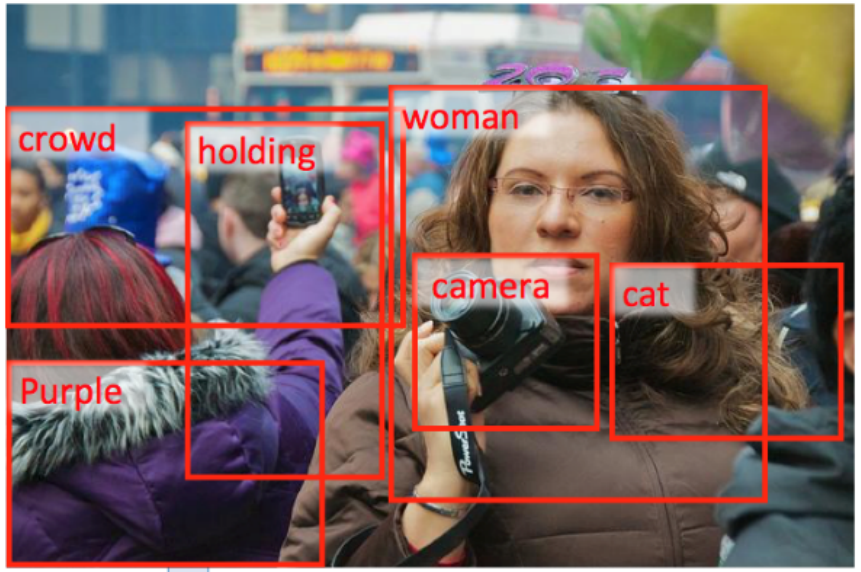
- Syntactic Parsing
- Word Sense Disambiguation
- Sentiment Analysis
- Topic Modeling
- Information Retrieval

Hard

- Machine Translation
- Text Generation
- Automatic Summarization
- Question Answering
- Conversational Interfaces

Interdisciplinary Tasks: Speech-to-Text

Interdisciplinary Tasks: Image Captioning



1. detect words → woman, crowd, cat, camera, holding, purple

2. generate sentences → A purple camera with a woman. A woman holding a camera in a crowd. ... A woman holding a cat.

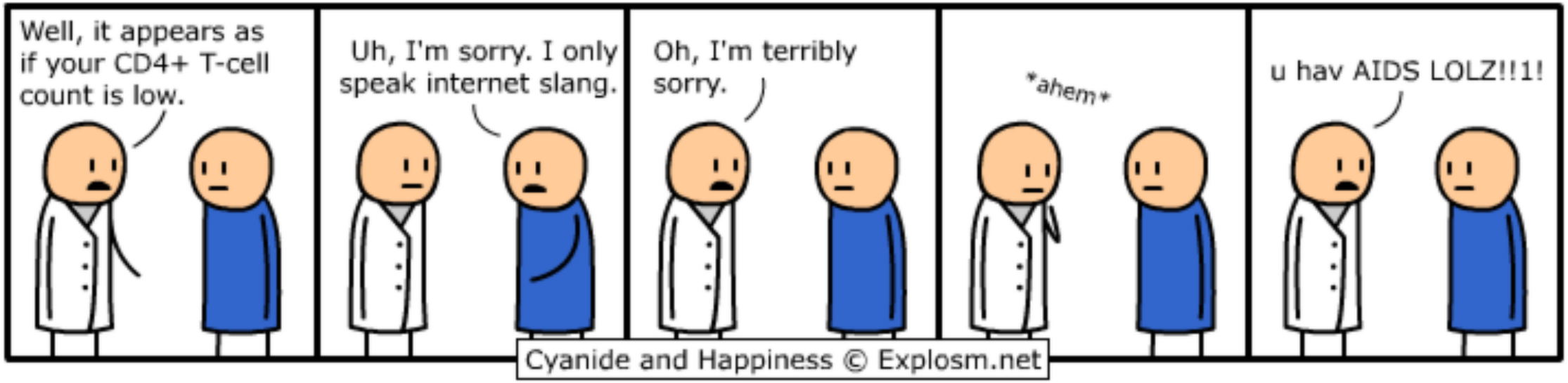
3. re-rank sentences → #1 A woman holding a camera in a crowd.

What Makes NLP so Hard?

Ambiguity


what are you watching?
–
nothing.
–
Pornhub
the world's biggest archive of nothing.

Non-Standard Language



Also: neologisms, complex entity names, phrasal verbs/idioms

More Complex Languages Than English

- **German:** Donaudampfschiffahrtsgesellschaftskapitän (5 “words”)
- **Chinese:** 50,000 different characters (2-3k to read a newspaper)
- **Japanese:** 3 writing systems
- **Thai:** Ambiguous word boundaries and sentence concepts
- **Slavic:** Different word forms depending on gender, case, tense

Write Traditional “If-Then-Else” Rules?

BIG NOPE!

Leads to very large and complex codebases.

Still struggles to capture trivial cases (for a human).

Better Approach: Machine Learning

> • A computer program is said to learn from experience **E**
> • with respect to some class of tasks **T** and performance measure **P**,
> • if its performance at tasks in **T**, as measured by **P**,
> • improves with experience **E**.
>
> — Tom M. Mitchell

PART 1

ESSENTIAL MACHINE LEARNING BACKGROUND FOR NLP

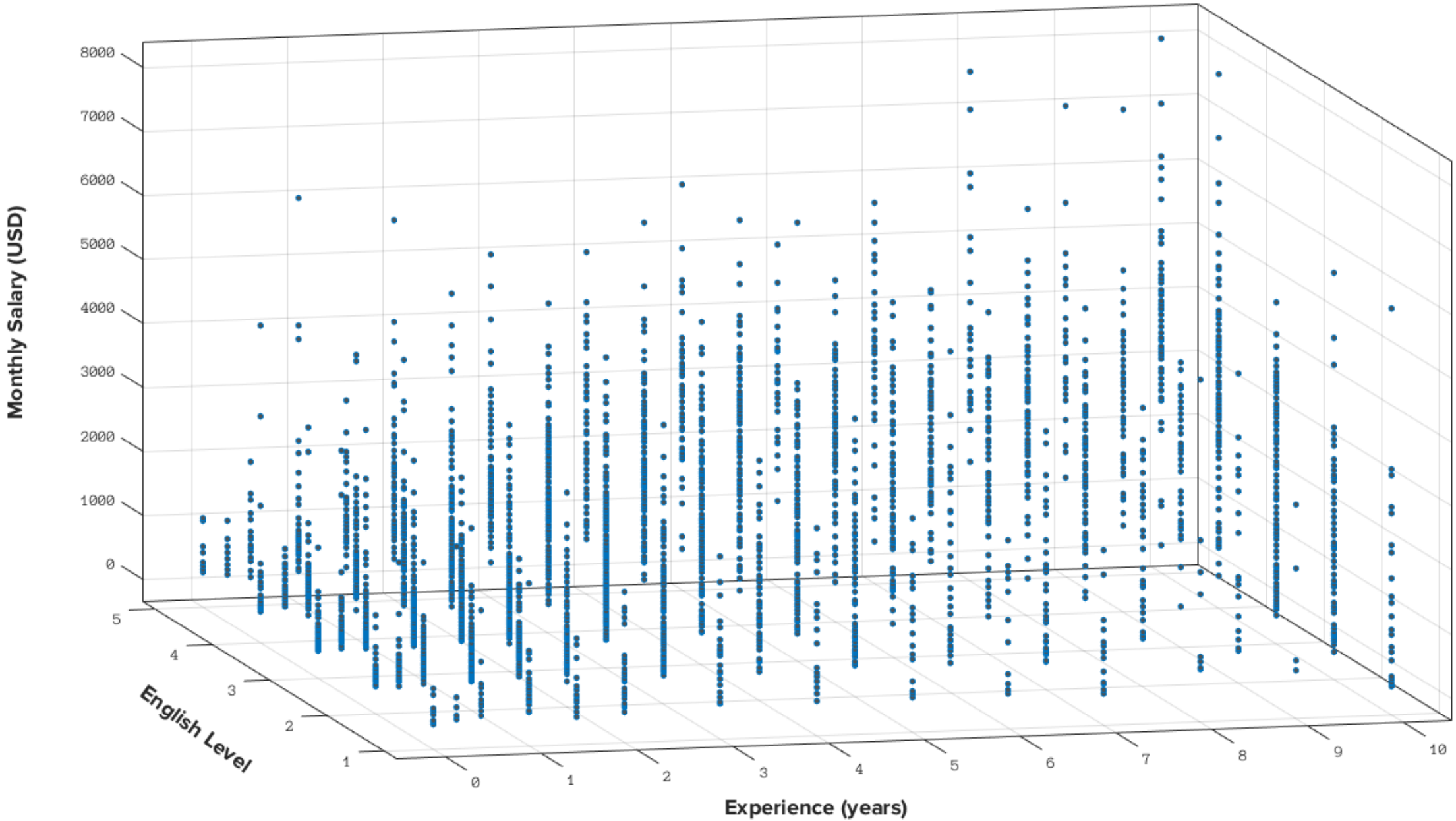
NLP MORNING @ LOHIKA

Before We Begin: Disclaimer

- This will be a very quick description of ML. By no means exhaustive.
- Only the essential background for what we'll have in Part 2.
- To fit everything into a small timeframe, I'll simplify some aspects.
- I encourage you to read ML books or watch videos to dig deeper.

Common ML Tasks

1. **Supervised Learning**
    - Regression
    - Classification (Binary or Multi-Class)
2. **Unsupervised Learning**
    - Clustering
    - Anomaly Detection
    - Latent Variable Models (Dimensionality Reduction, EM, ...)


Monthly Salary (USD)
8000
7000
6000
5000
4000
3000
2000
1000
0
English Level
5
4
3
2
1
Experience (years)
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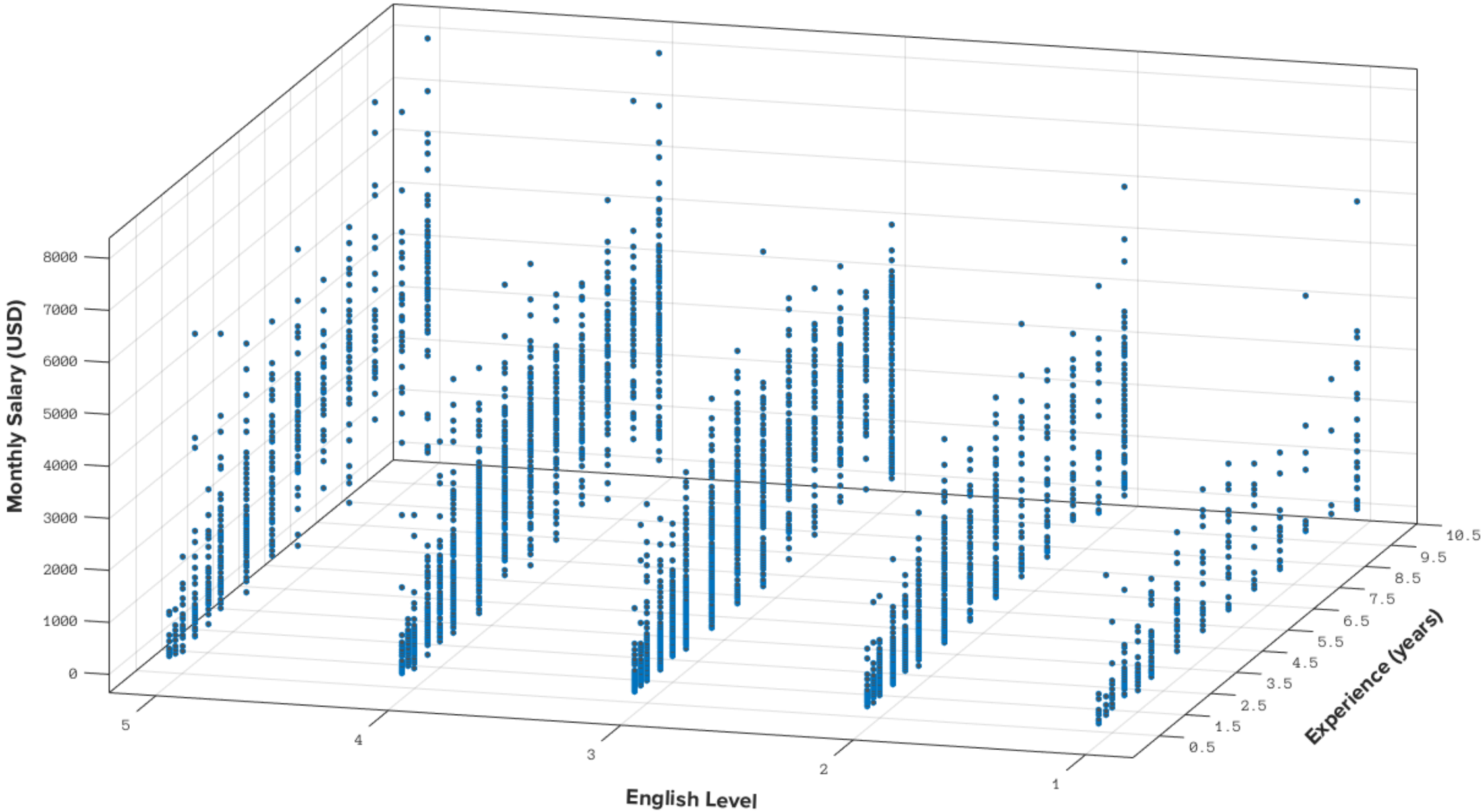
1
2
3
4
5
6
7
8
9
10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English Level
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9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
Experience (years)

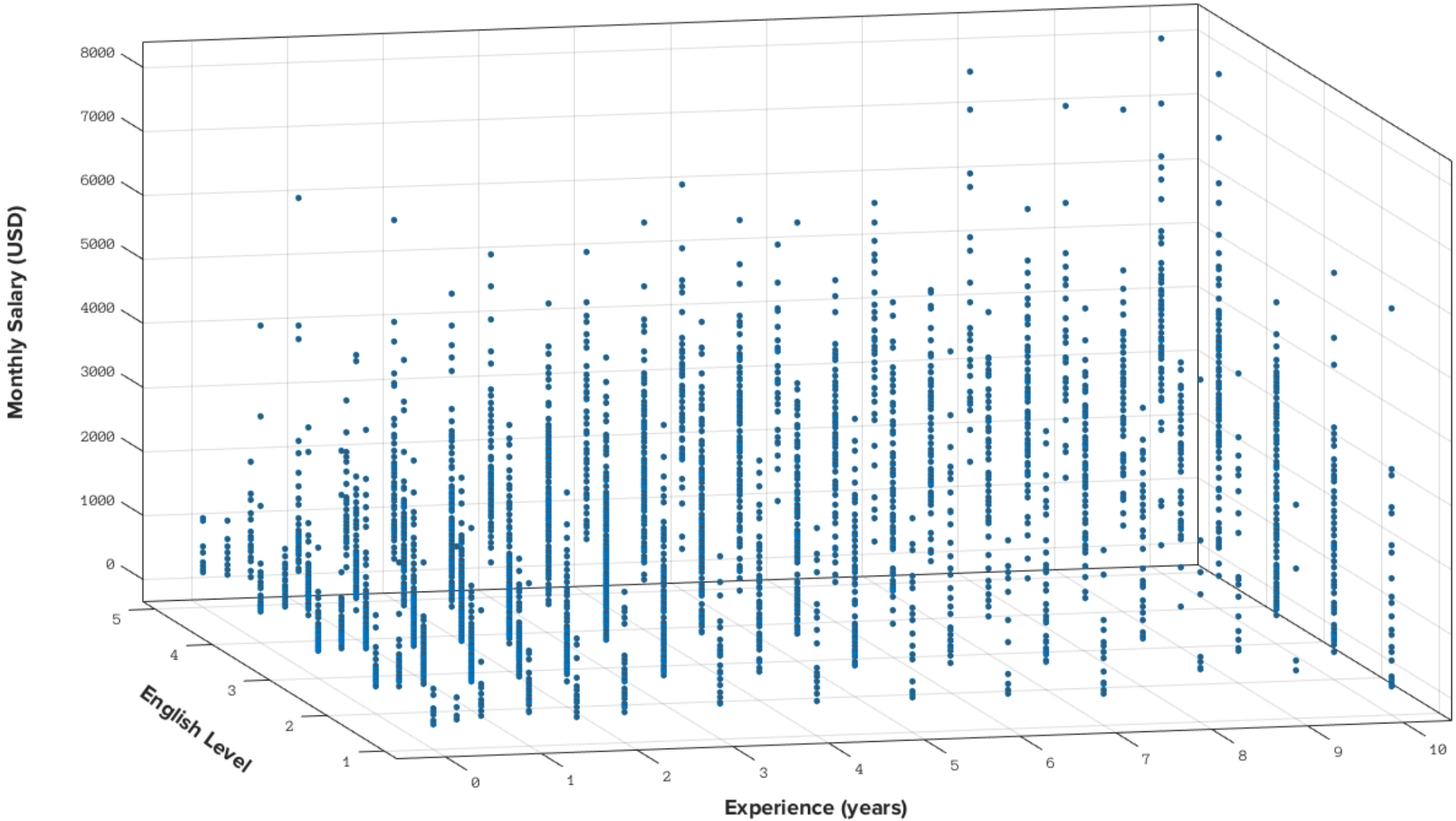
Regression

Predict a continuous dependent variable
based on independent predictors

$$\text{Salary} = \theta_1 \cdot \text{Experience} + \theta_2 \cdot \text{EnglishLevel} + \theta_3$$

$$y = \theta_1 \cdot x_1 + \theta_2 \cdot x_2 + \theta_3 = \theta^T x$$

$$h_\theta(x) = \theta^T x$$


Monthly Salary (USD)
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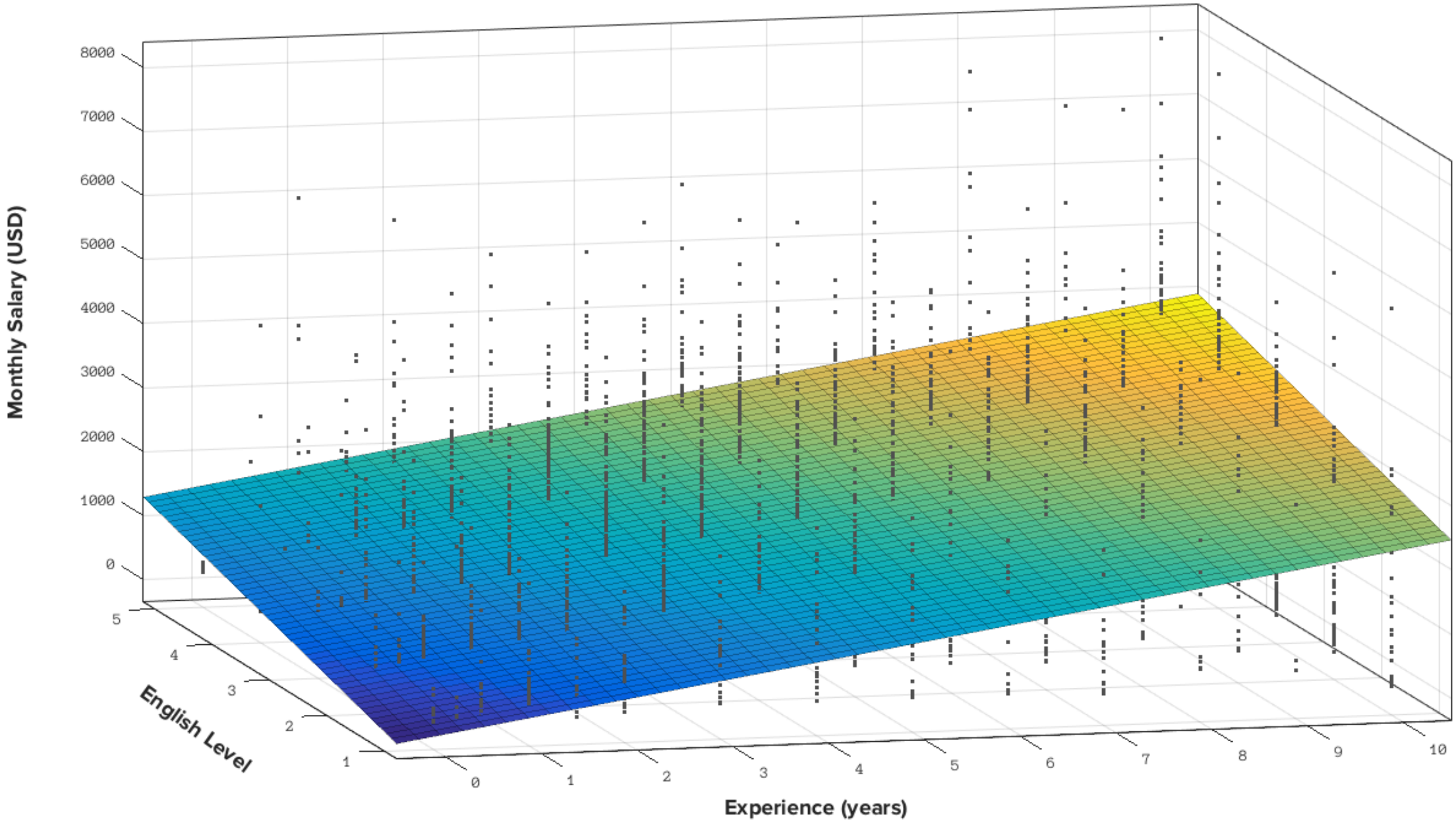
Monthly Salary (USD)
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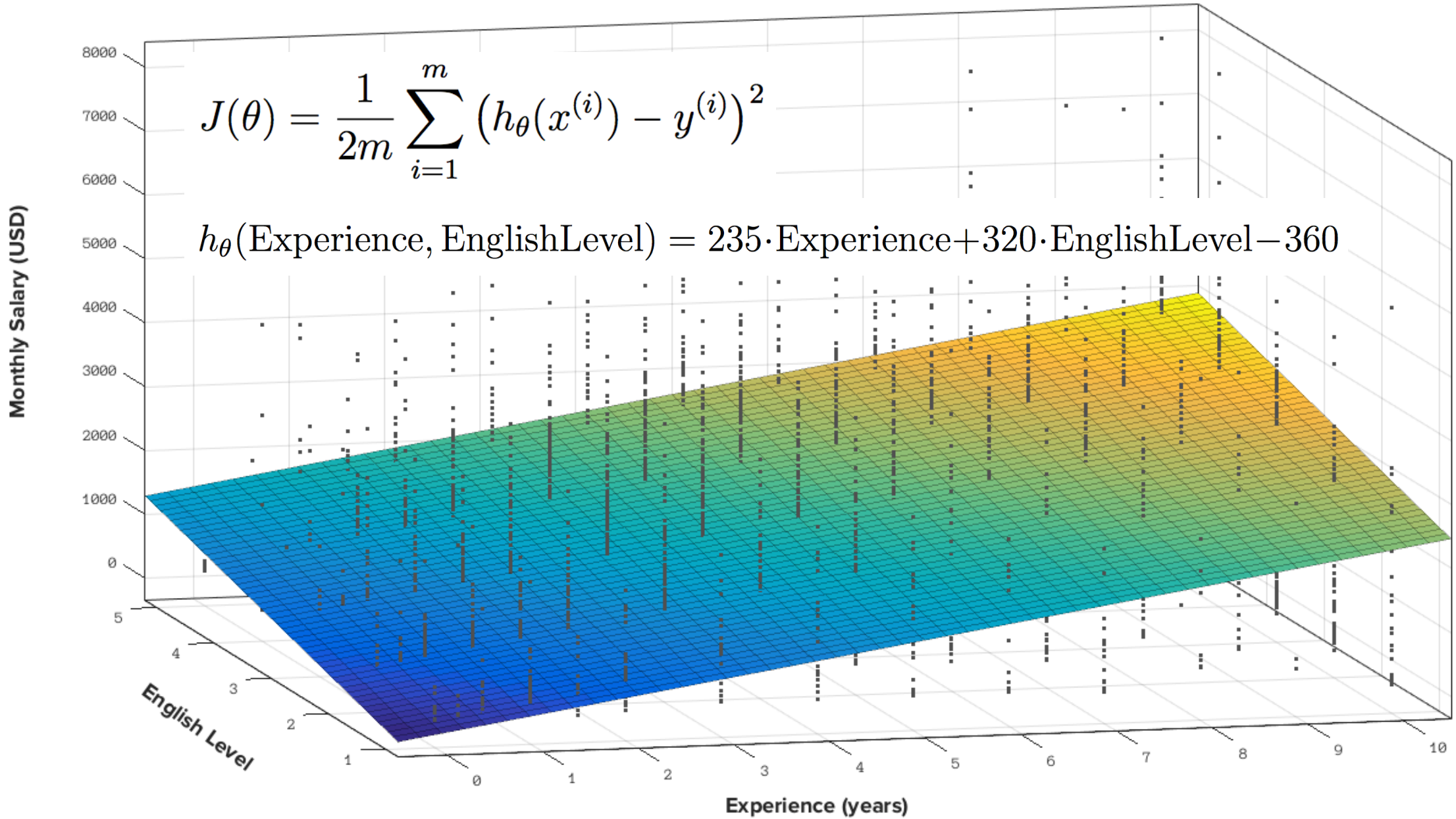
0
English Level
5
4
3
2
1
Experience (years)
0
1
2
3
4
5
6
7
8
9
10

Linear Regression

$$h_\theta(x) = \theta^T x$$

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$$


$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$
$h_\theta(\text{Experience}, \text{EnglishLevel}) = 235 \cdot \text{Experience} + 320 \cdot \text{EnglishLevel} - 360$
Monthly Salary (USD)
8000
7000
6000
5000
4000
3000
2000
1000
0
English Level
5
4
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1
Experience (years)
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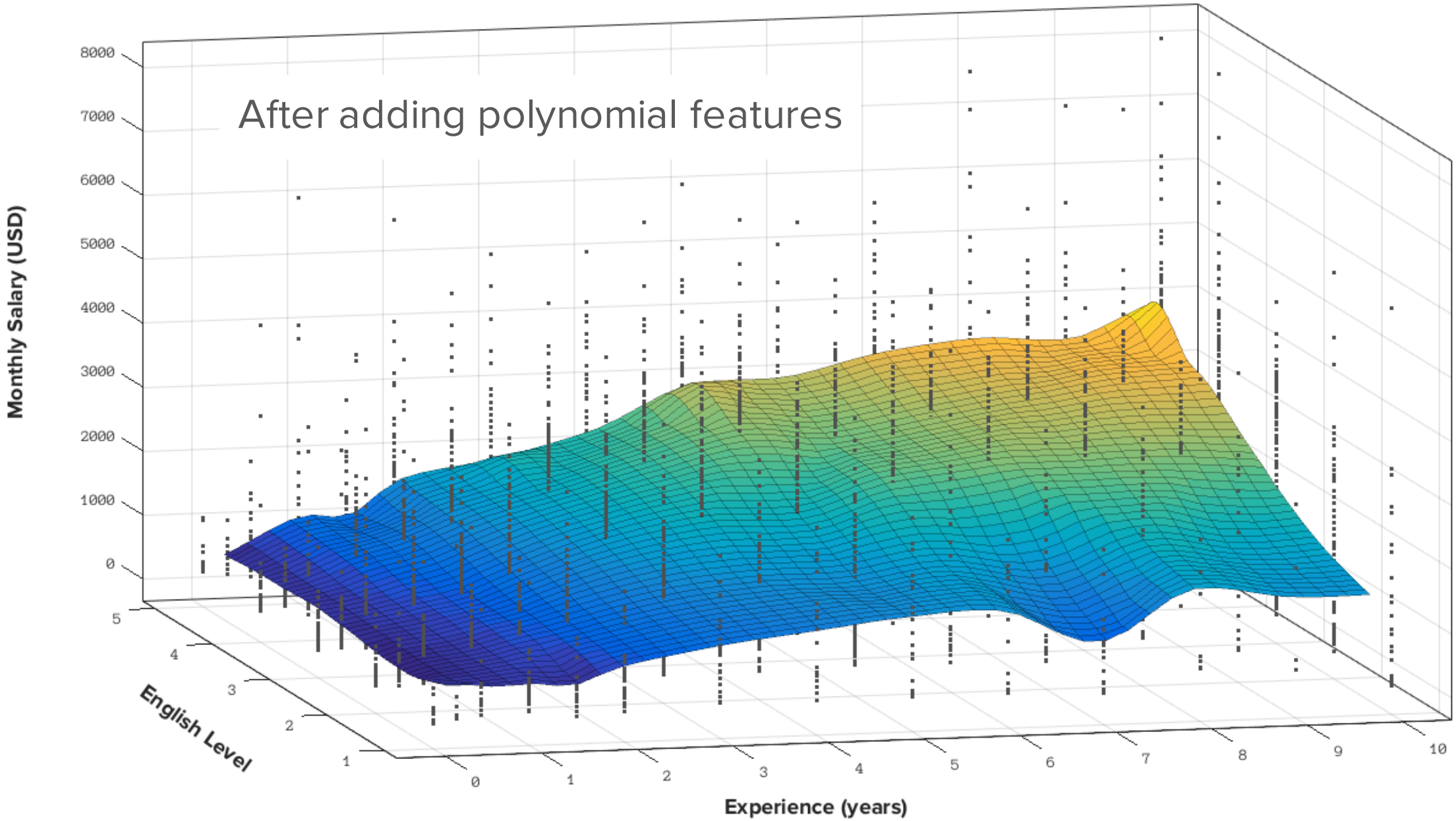

After adding polynomial features
Monthly Salary (USD)
8000
7000
6000
5000
4000
3000
2000
1000
0
English Level
5
4
3
2
1
Experience (years)
0
1
2
3
4
5
6
7
8
9
10

$$X = \begin{bmatrix} \text{AliceExperience} & \text{AliceEnglishLevel} & \dots \\ \text{BobExperience} & \text{BobEnglishLevel} & \dots \\ \text{CharlieExperience} & \text{CharlieEnglishLevel} & \dots \\ \dots & \dots & \dots \end{bmatrix} \qquad y = \begin{bmatrix} \text{AliceSalary} \\ \text{BobSalary} \\ \text{CharlieSalary} \\ \dots \end{bmatrix}$$

Learn model parameters (θ) by optimizing the objective function $J(\theta)$

$$y_{unknown} = h_\theta(X_{unknown}) = X_{unknown}\theta$$

Classification

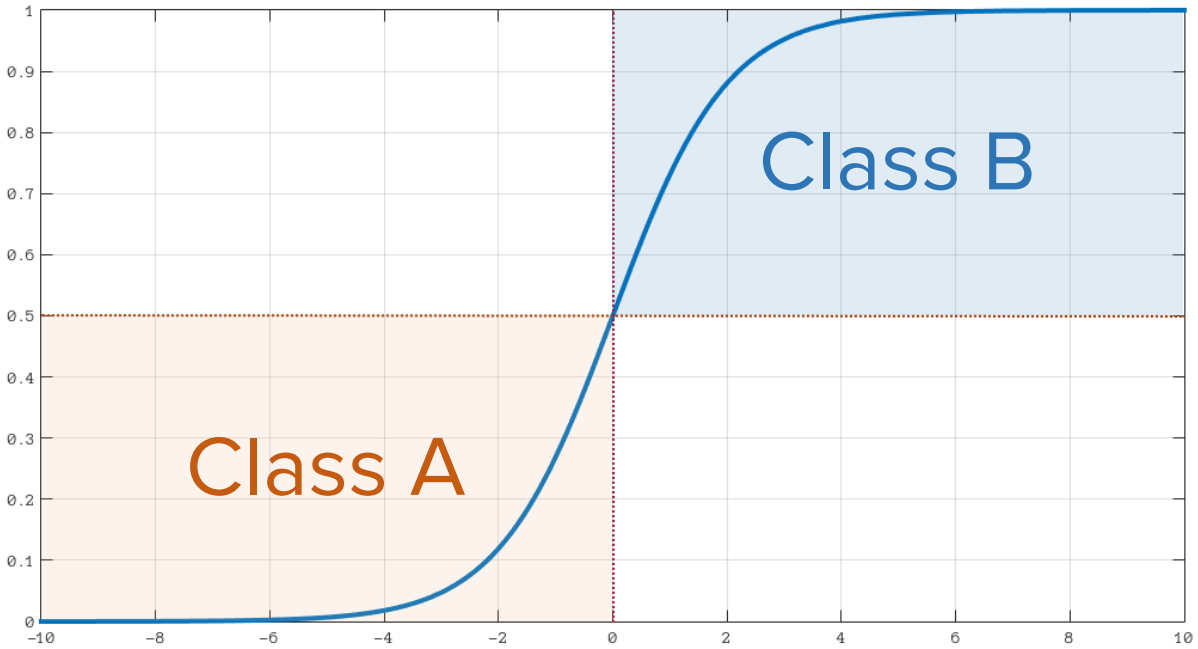
Assign an observation to some category
from a known discrete list of categories

Logistic Regression

(Multi-class extension = Softmax Regression)

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

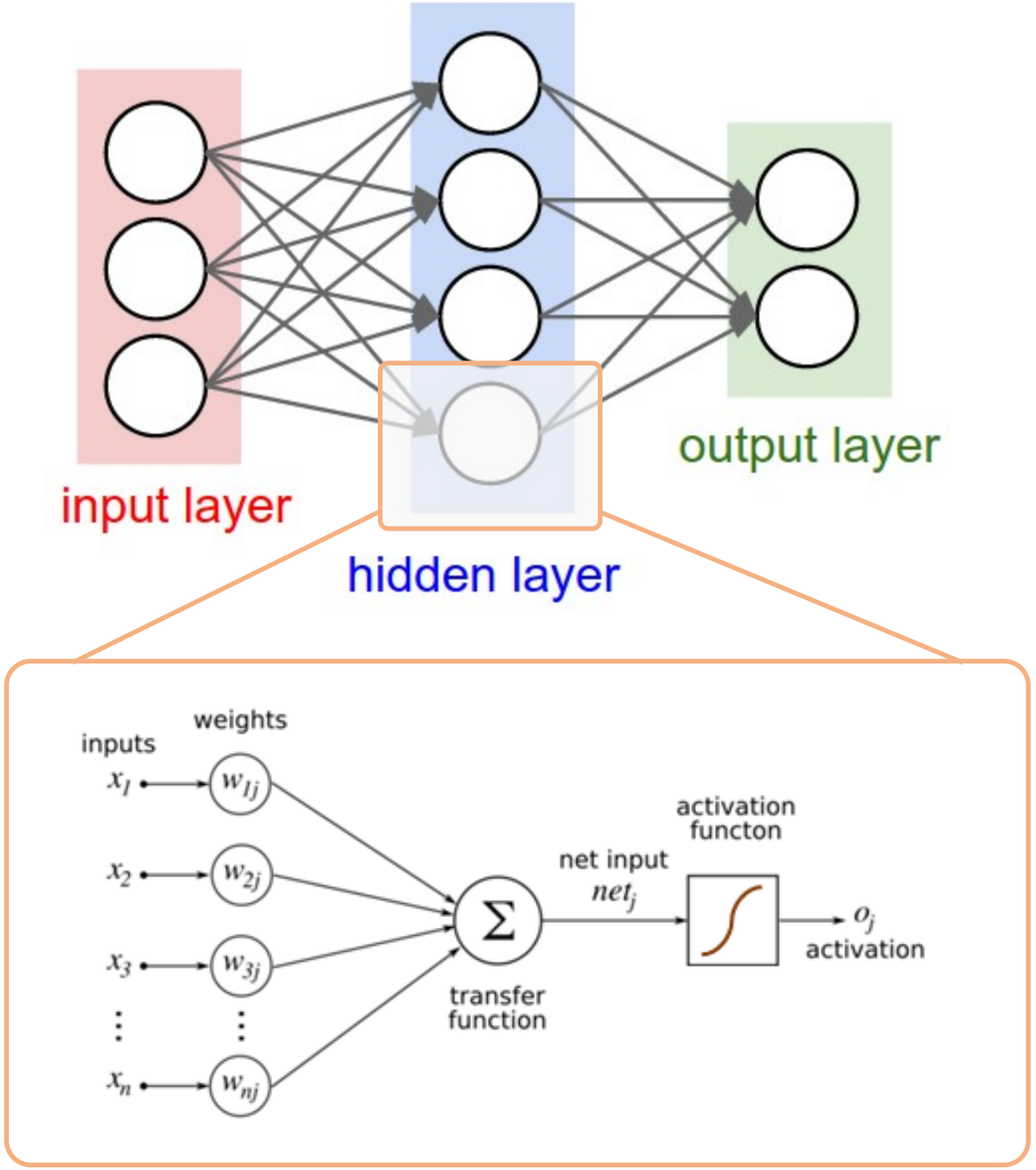
$$h_\theta(x) = \sigma(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$

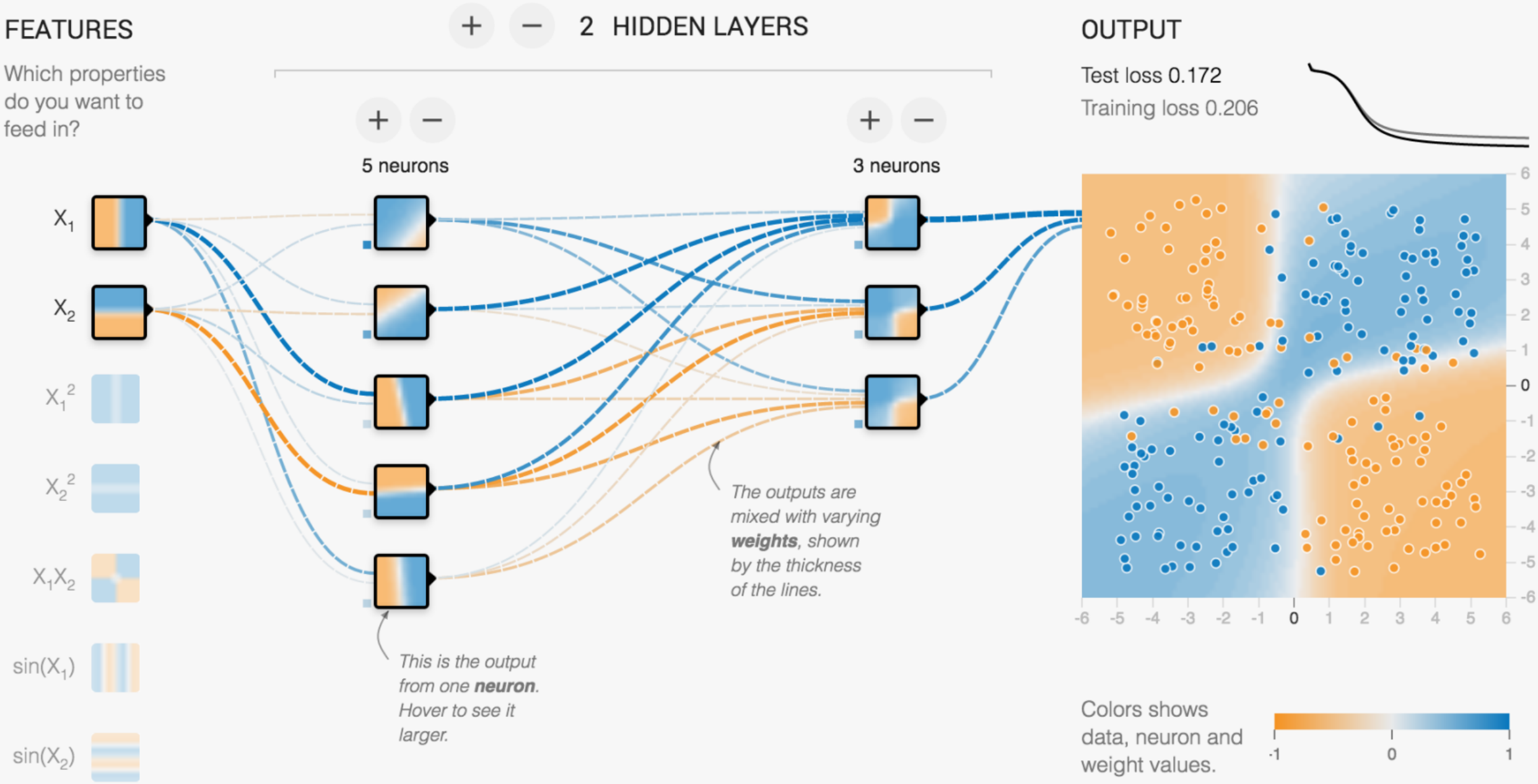


$$J(\theta) = \frac{1}{m}\left[\sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))\right]$$

Neural Networks

and Backpropagation Algorithm

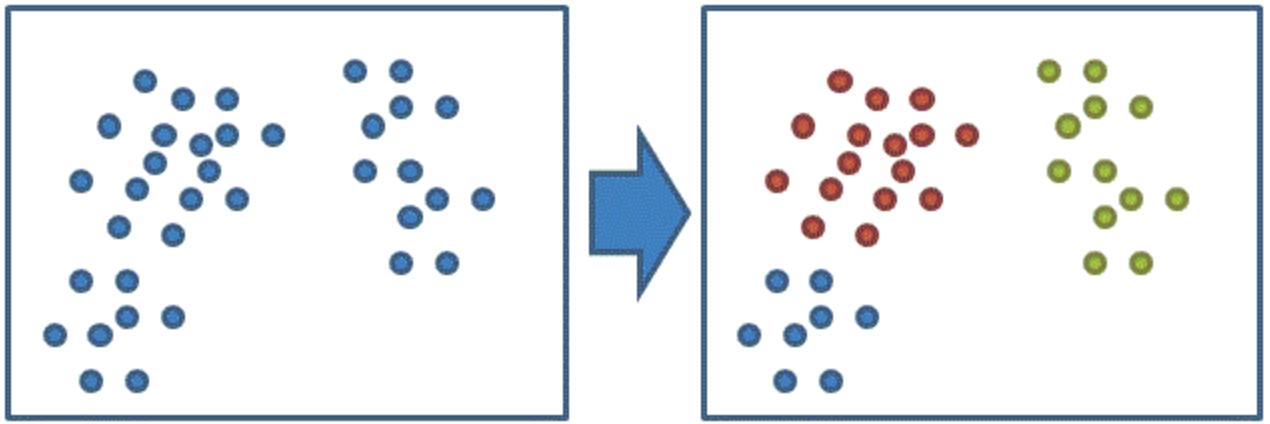




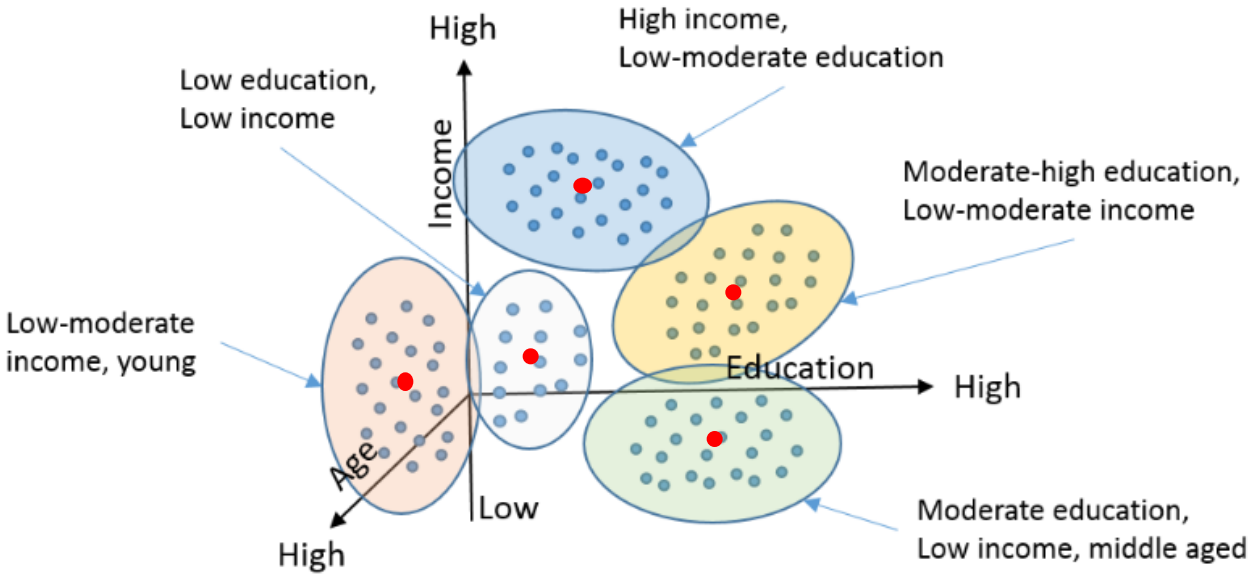
http://playground.tensorflow.org/

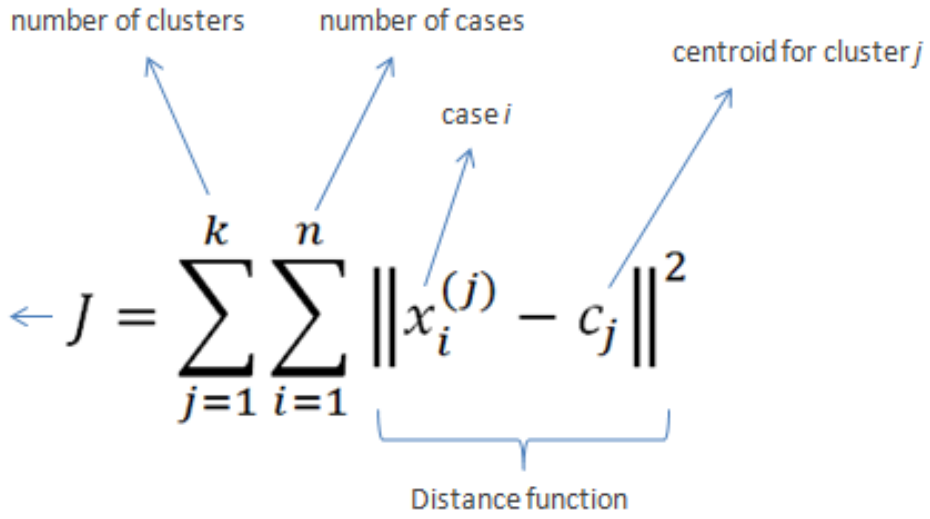
Clustering

Group objects in such a way
that objects in the **same** group are **similar**,
and objects in the **different** groups are **not**



K-Means Clustering



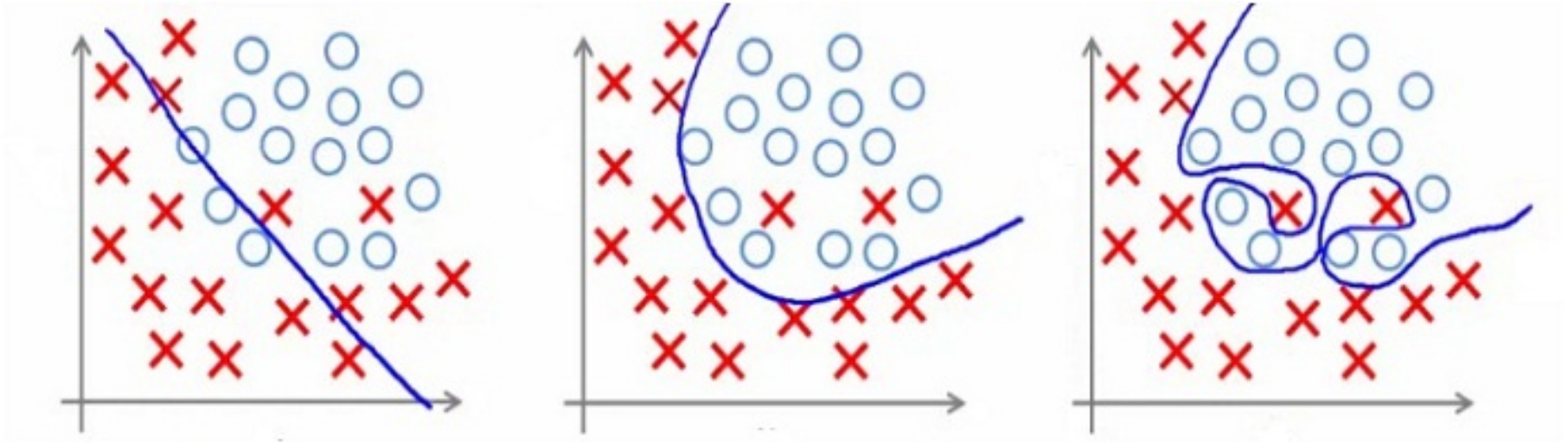


Evaluation

How do we know if an ML model is good?

What do we do if something goes wrong?

Underfitting & Overfitting



Under-fitting

(too simple to explain the variance)

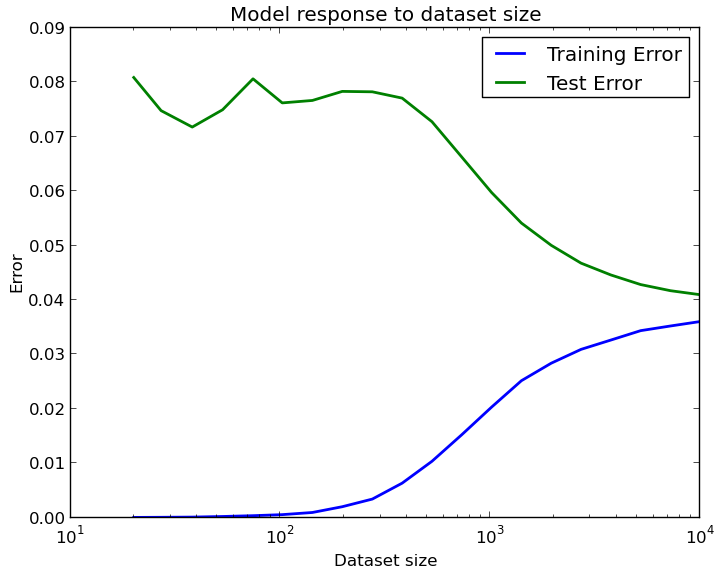
Appropriate-fitting

Over-fitting

(forcefitting -- too good to be true)

Development & Troubleshooting

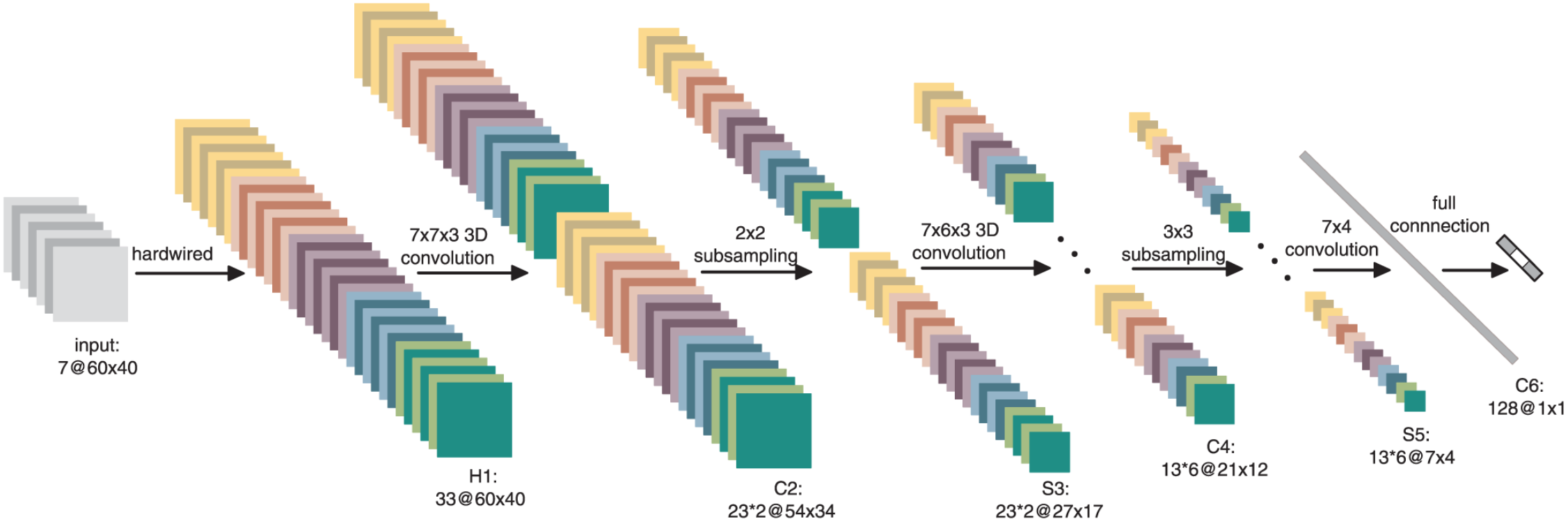
- Picking the right metric: MAE, RMSE, AUC, Cross-Entropy, Log-Loss
- Training Set / Validation Set / Test Set split
- Picking hyperparameters against Validation Set
- Regularization to prevent OF
- Plotting learning curves to check for UF/OF



Deep Learning

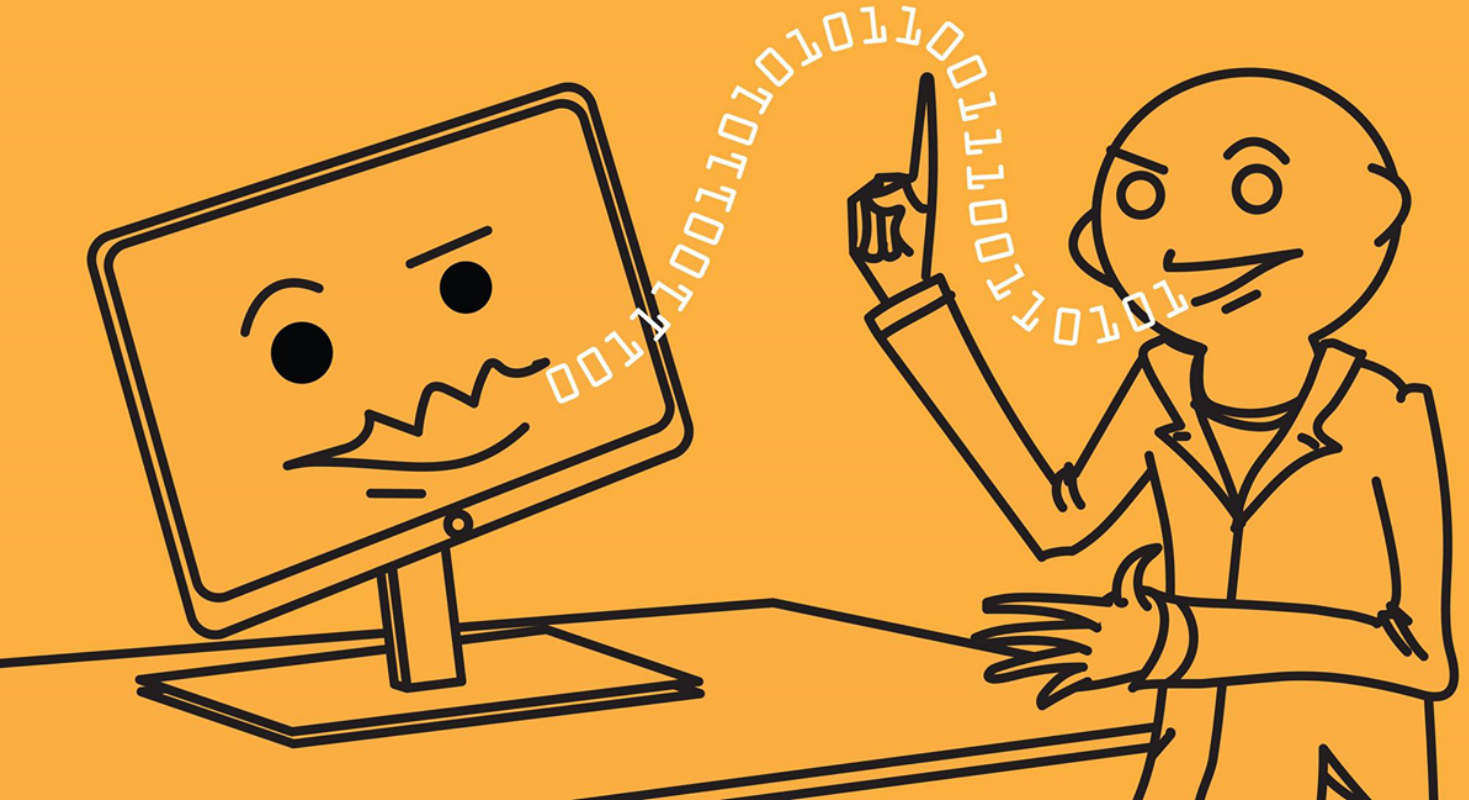
- Core idea: instead of hand-crafting complex features, use increased computing capacity and build a deep computation graph that will try to **learn feature representations on its own**.
  End-to-end learning rather than a cascade of apps.
- Works best with lots of **homogeneous**, **spatially related** features (image pixels, character sequences, audio signal measurements).
  Usually works **poorly otherwise**.
- State-of-the-art and/or superhuman performance on many tasks.
- Typically requires **massive** amounts of data and training resources.
- But: a very young field. Theories not strongly established, views change.

Example: Convolutional Neural Network



PART 2

NLP CHALLENGES AND APPROACHES



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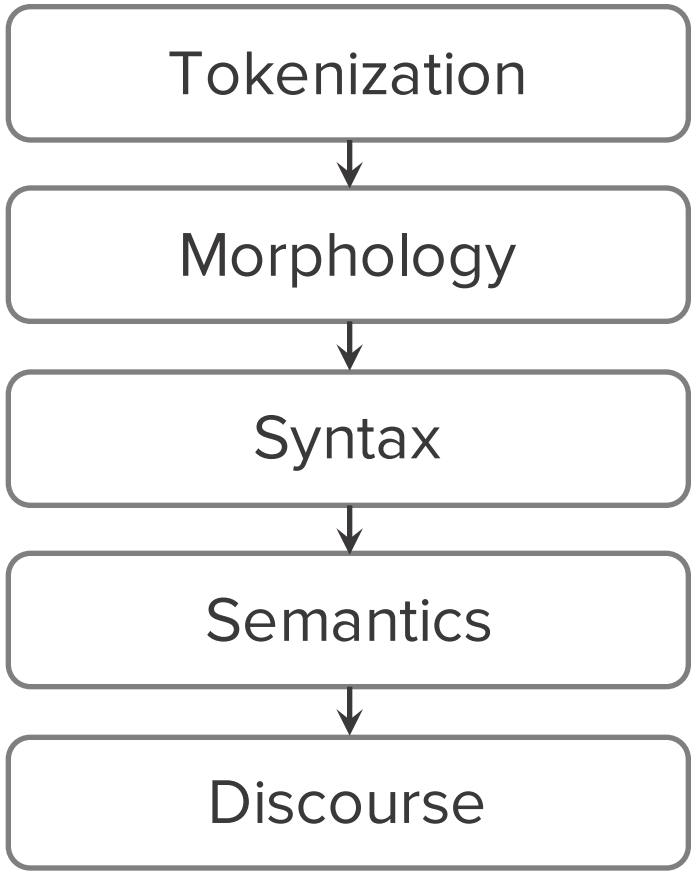
“Classical” NLP Pipeline



Break text into sentences and words, lemmatize

Part of speech (POS) tagging, stemming, NER

Constituency/dependency parsing

Coreference resolution, wordsense disambiguation

Task-dependent (sentiment, …)

Often Relies on Language Banks

- WordNet (ontology, semantic similarity tree)
- Penn Treebank (POS, grammar rules)
- PropBank (semantic propositions)
- …Dozens of them!

Tokenization & Stemming

```
In [1]: import nltk
```

```
In [2]: nltk.download(["punkt", "averaged_perceptron_tagger", "treebank",
                       "maxent_ne_chunker", "words", "wordnet"])
```

...

```
In [3]: text = open("data/clean/asoiaf01.txt").read()
```

```
In [4]: sentences = nltk.tokenize.sent_tokenize(text)
```

```
In [5]: sentences[5313]
```

```
Out[5]: 'Cersei Lannister regarded him suspiciously.'
```

```
In [6]: sentences = [nltk.tokenize.word_tokenize(sentence) for sentence in sentences]
```

```
In [7]: sentences[5313]
```

```
Out[7]: ['Cersei', 'Lannister', 'regarded', 'him', 'suspiciously', '.']
```

```
In [8]: stemmer = nltk.stem.SnowballStemmer(language="english")
        [stemmer.stem(word) for word in sentences[5313]]
```

```
Out[8]: ['cersei', 'lannist', 'regard', 'him', 'suspici', '.']
```

POS/NER Tagging

```
In [10]: tagged_sentence = nltk.pos_tag(sentences[5313])

In [11]: tagged_sentence

Out[11]: [('Cersei', 'NNP'),
          ('Lannister', 'NNP'),
          ('regarded', 'VBD'),
          ('him', 'PRP'),
          ('suspiciously', 'RB'),
          ('.', '.')]

In [12]: lemmatizer = nltk.stem.wordnet.WordNetLemmatizer()
         [lemmatizer.lemmatize(word, pos=penn_to_wn(tag)) for word, tag in tagged_sentence]

Out[12]: ['Cersei', 'Lannister', 'regard', 'him', 'suspiciously', '.']

In [13]: tree = nltk.ne_chunk(tagged_sentence)

In [14]: tree.draw()
```

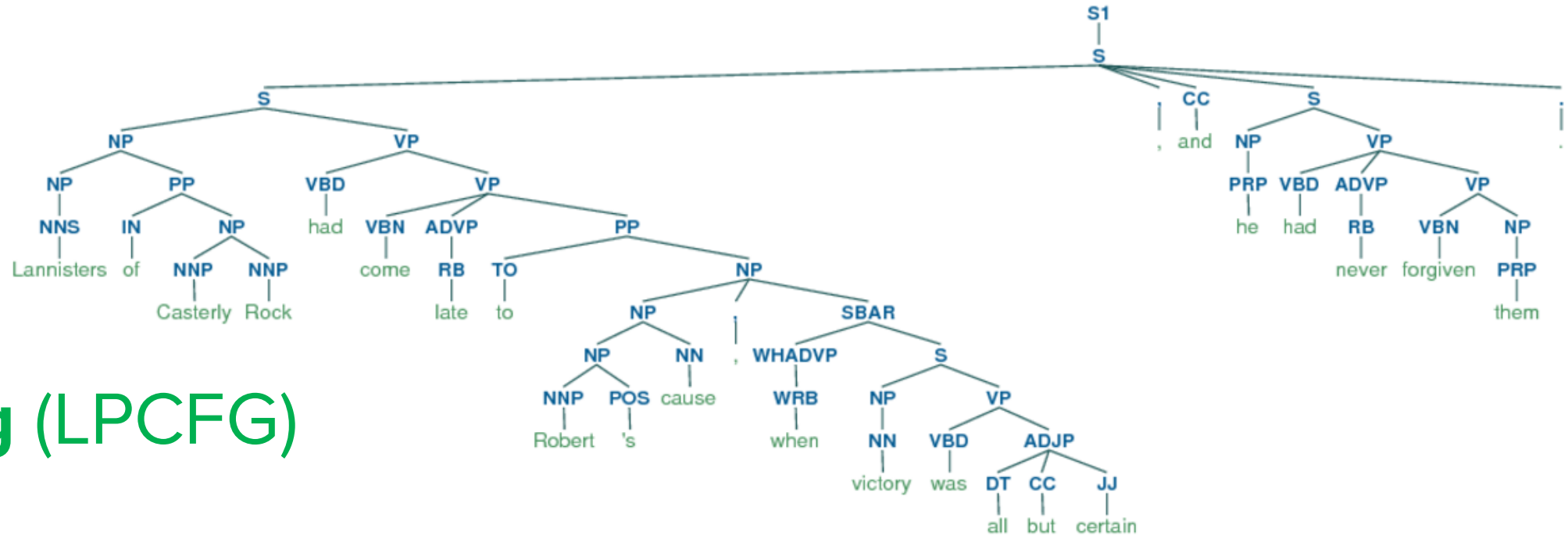
```
In [1]: import bllipparser
```

```
In [2]: model_dir = "/home/yuriyguts/nltk_data/models/bllip_wsj_no_aux"
        parser = bllipparser.RerankingParser.from_unified_model_dir(model_dir)
```

```
In [3]: sentence = "Lannisters of Casterly Rock had come late to Robert's cause, "\
                   "when victory was all but certain, and he had never forgiven them."
```

```
In [4]: best_parse_tree = parser.parse(sentence)[0].ptb_parse
```

```
In [5]: best_parse_tree.as_nltk_tree().draw()
```



Parsing (LPCFG)

“Classical” way: Training a NER Tagger

Task: Predict whether the word is a **PERSON**, **LOCATION**, **DATE** or **OTHER**.

Could be more than 3 NER tags (e.g. MUC-7 contains 7 tags).

Features:

1. Current word.
2. Previous, next word (context).
3. POS tags of current word and nearby words.
4. NER label for previous word.
5. Word substrings (e.g. ends in “burg”, contains “oxa” etc.)
6. Word shape (internal capitalization, numerals, dashes etc.).
7. ...on and on and on...

Feature Representation: Bag of Words

A single word is a one-hot encoding vector with the size of the dictionary :(

Problem

- Manually designed features are often over-specified, incomplete, take a long time to design and validate.
- Often requires PhD-level knowledge of the domain.
- Researchers spend literally decades hand-crafting features.
- Bag of words model is very high-dimensional and sparse, cannot capture semantics or morphology.

Maybe **Deep Learning** can help?

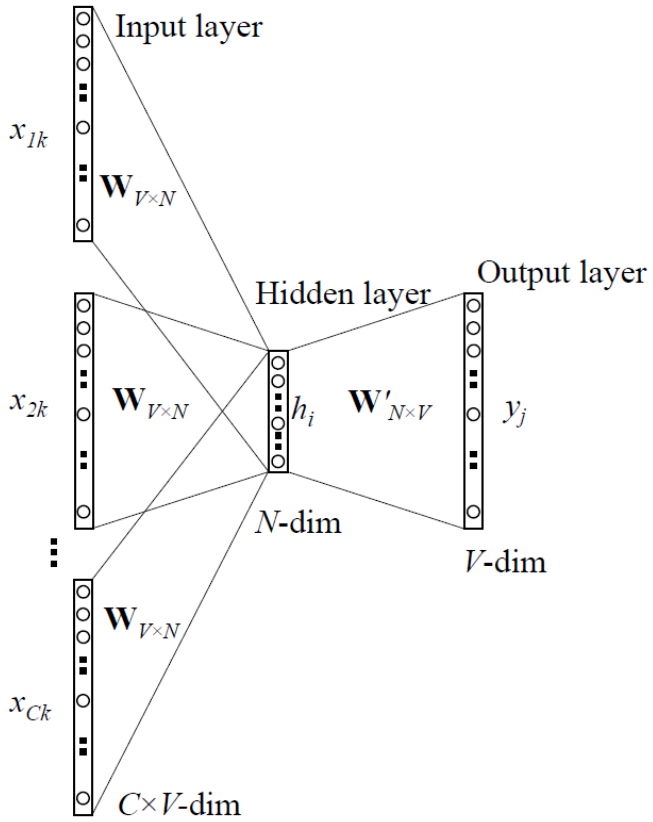
Deep Learning for NLP

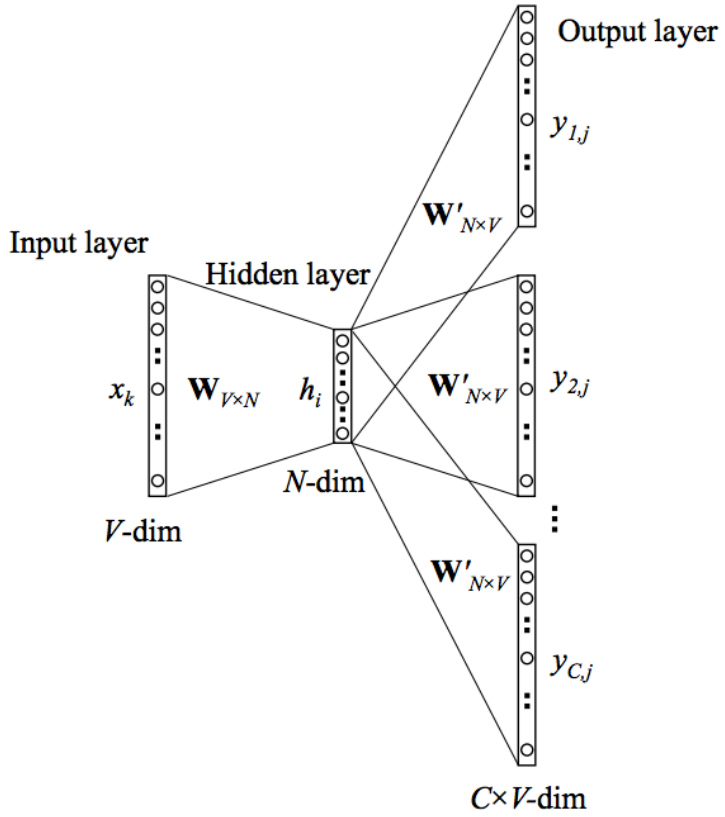
- Core enabling idea: represent words as **dense vectors**

  ~~[0 1 0 0 0 0 0 0 0 0]~~ [0.315 0.136 0.831]

- Try to capture semantic and morphologic similarity so that the features for "similar" words are "similar"
  (e.g. closer in Euclidean space).
- Natural language is context dependent: use context for learning.
- Straightforward (but slow) way: build a co-occurrence matrix and SVD it.

Embedding Methods: Word2Vec





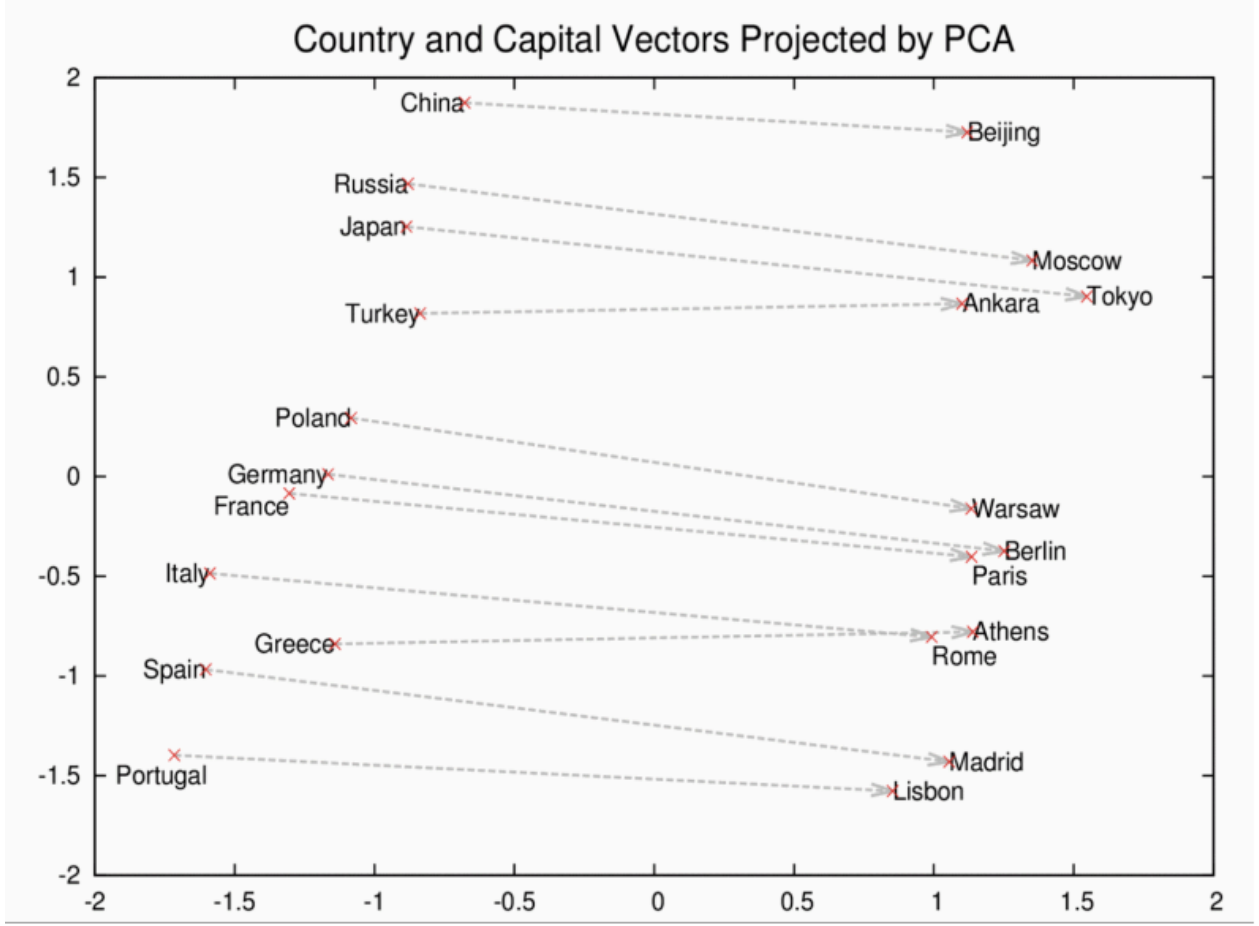
CBoW version: predict center word from context

Skip-gram version: predict context from center word

Benefits

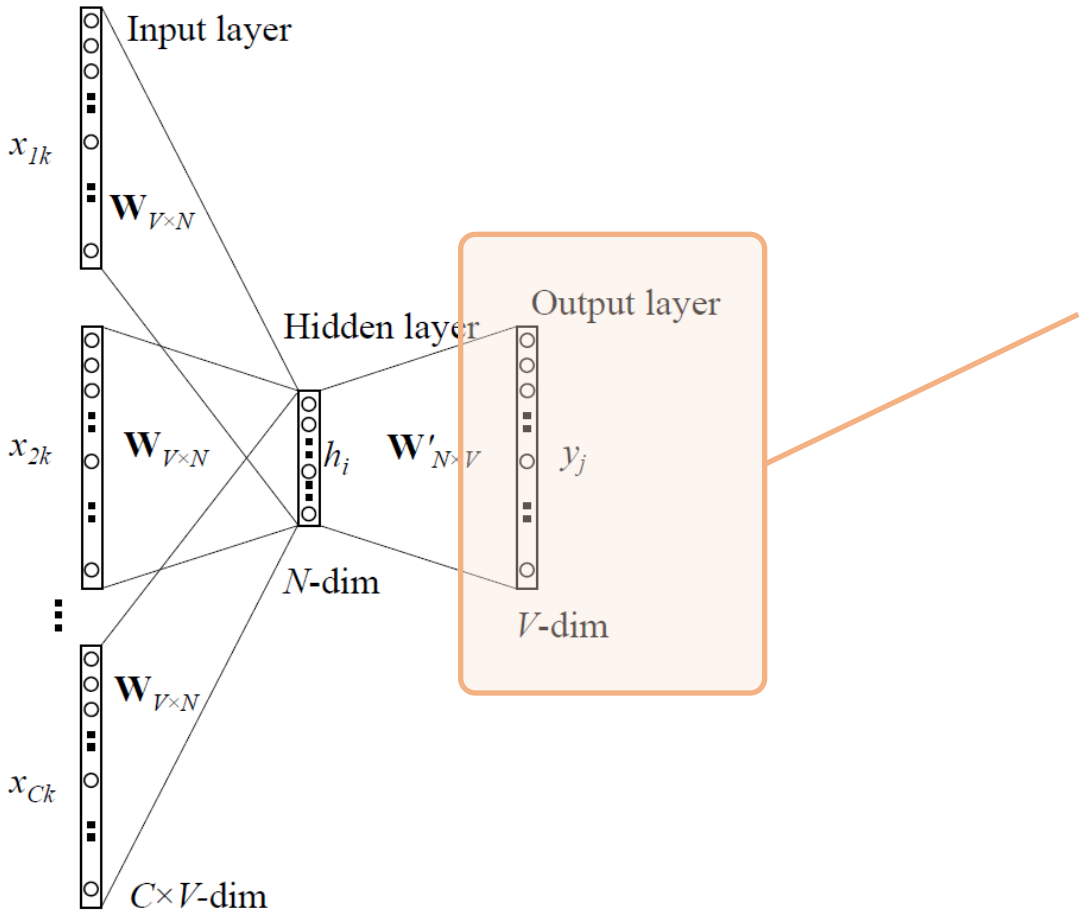
- Learns features of each word on its own, given a text corpus.
- No heavy preprocessing is required, just a corpus.
- Word vectors can be used as features for lots of supervised learning applications: POS, NER, chunking, semantic role labeling. All with pretty much the same network architecture.
- **Similarities and linear relationships between word vectors**.
- A bit more modern representation: GloVe, but requires more RAM.

Linearities



Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Training a NER Tagger: Deep Learning



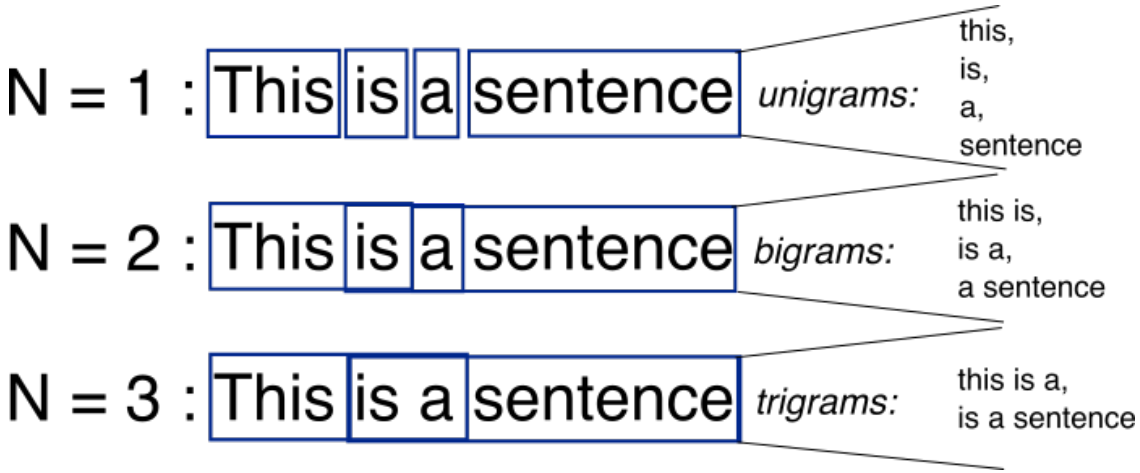
Just replace this with NER tag
(or POS tag, chunk end, etc.)

Language Modeling

Assign high probabilities to well-formed sentences

(crucial for text generation, speech recognition, machine translation)

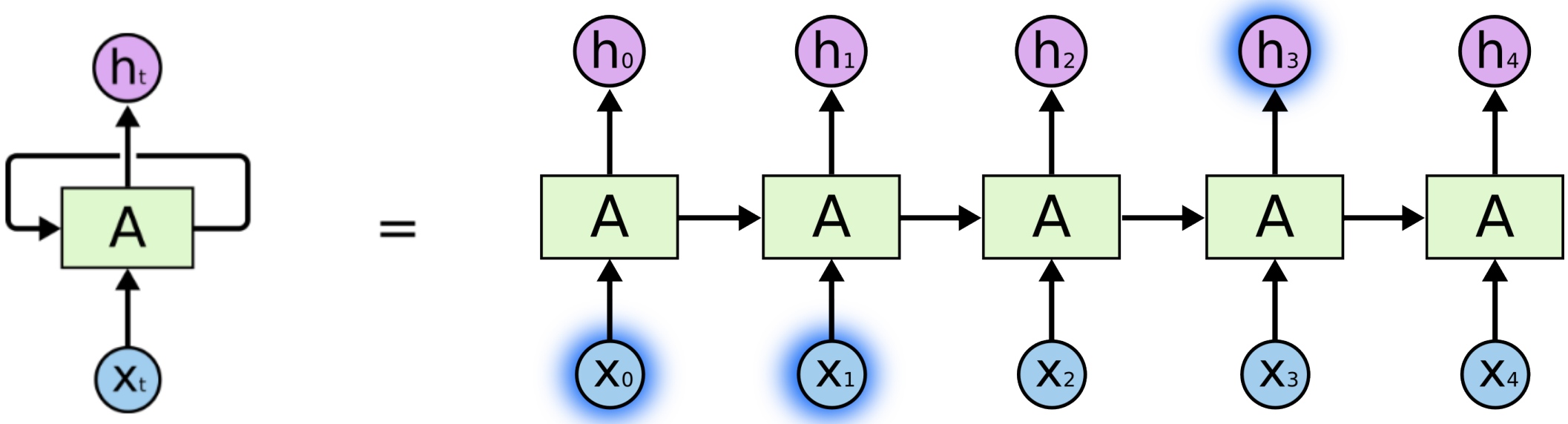
“Classical” Way: N-Grams



$$P(w_i|w_{i-k}^{i-1}) = \frac{count(w_{i-k}^{i}) + \alpha}{count(w_{i-k}^{i-1}) + \alpha V}$$

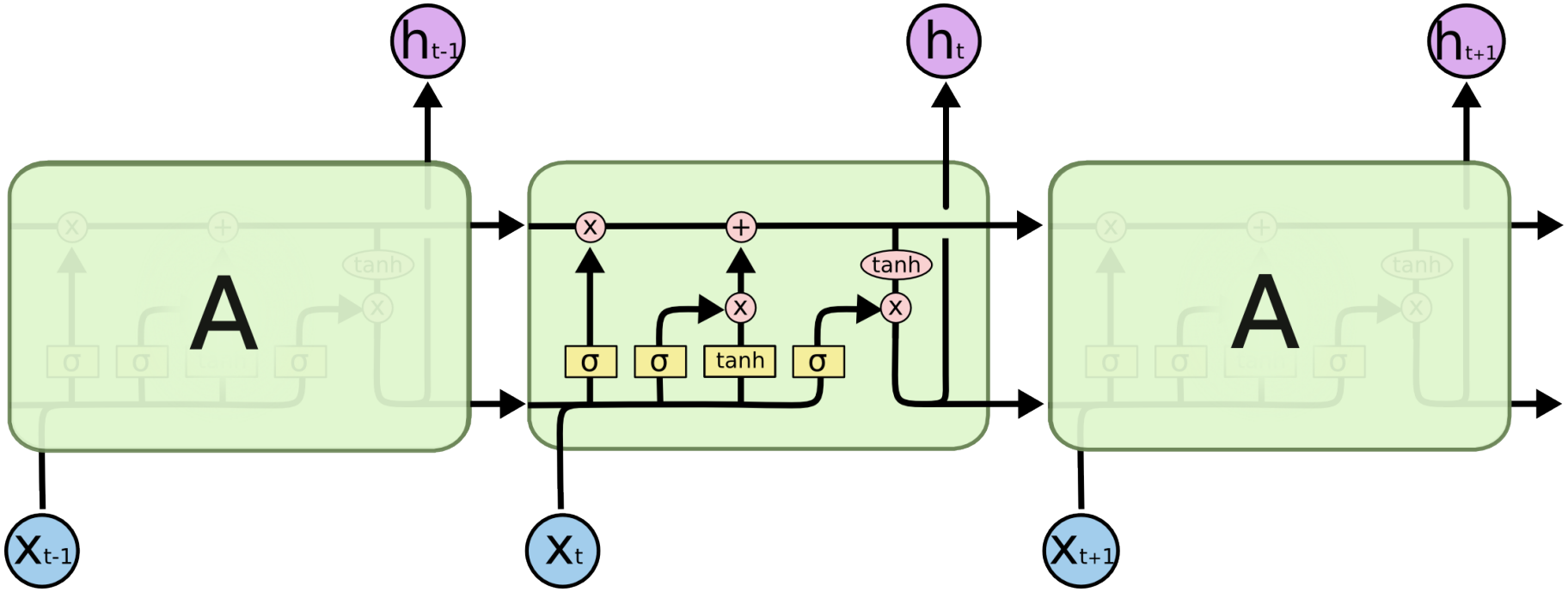
Problem: doesn’t scale well to bigger N. N = 5 is pretty much the limit.

Deep Learning Way: Recurrent NN (RNN)



Can use past information without restricting the size of the context.
But: in practice, can't recall information that came in a long time ago.

Long Short Term Memory Network (LSTM)

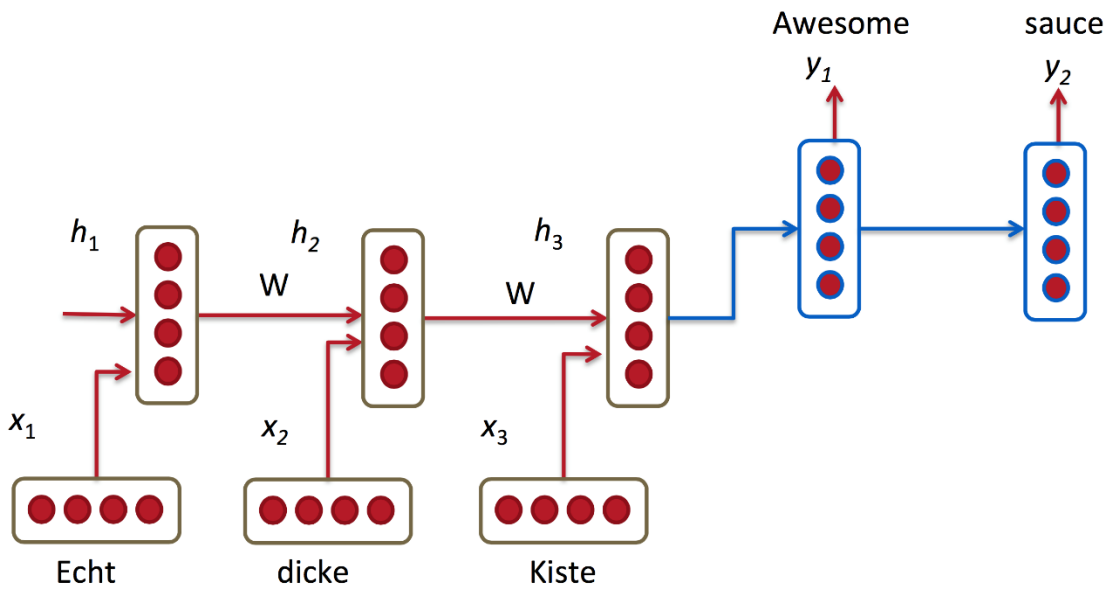


Contains gates that control forgetting, adding, updating and outputting information.
Surprisingly amazing performance at language tasks compared to vanilla RNN.

Tackling Hard Tasks

Deep Learning enables **end-to-end learning** for Machine Translation, Image Captioning, Text Generation, Summarization:

NLP tasks which are inherently very hard!



RNN for Machine Translation

Hottest Current Research

- Attention Networks
- Dynamic Memory Networks

(see ICML 2016 proceedings)

Tools I Used

- NLTK (Python)
- Gensim (Python)
- Stanford CoreNLP (Java with bindings)
- Apache OpenNLP (Java with bindings)

Deep Learning Frameworks with GPU Support:

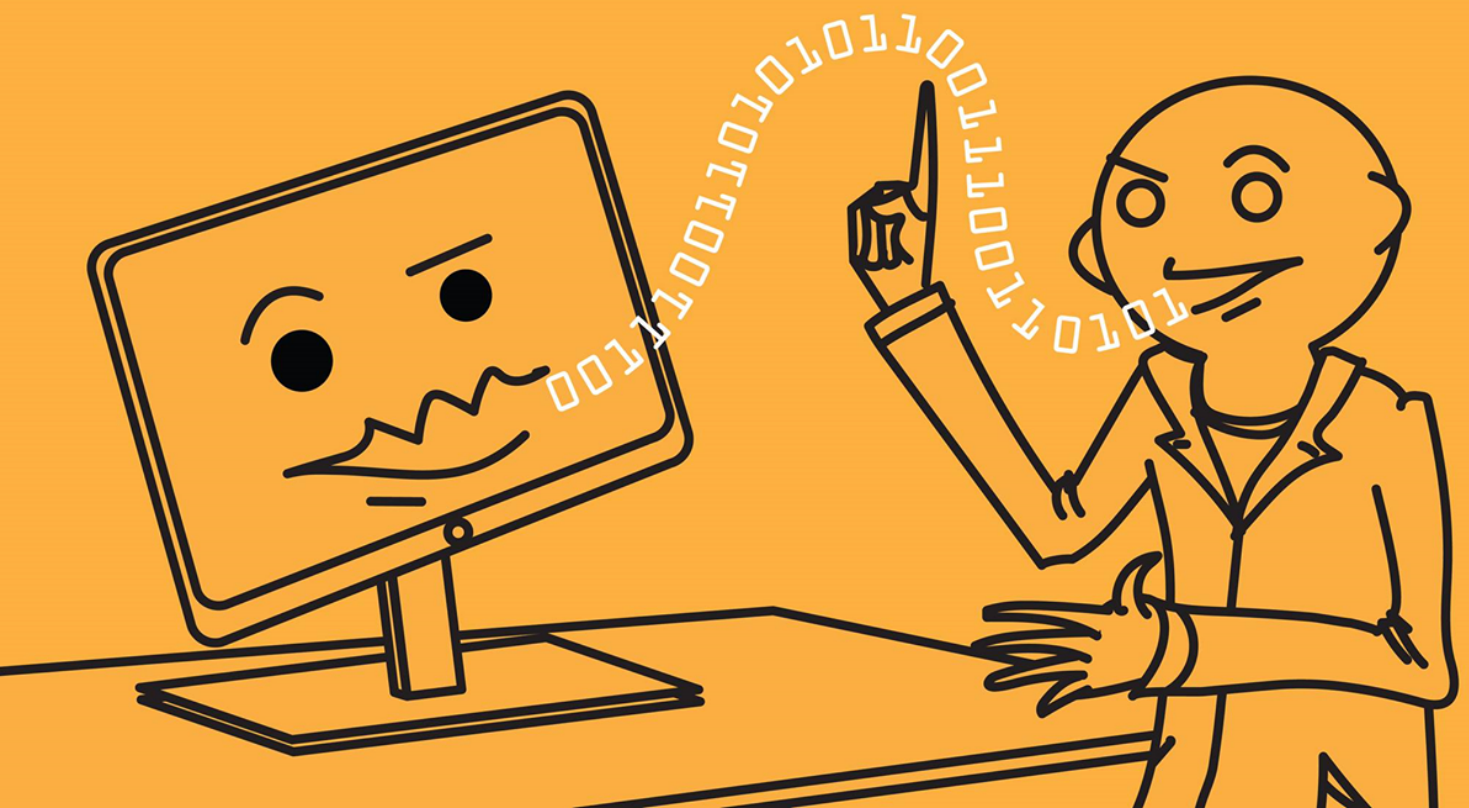
- Torch (Torch-RNN) (Lua)
- TensorFlow, Theano, Keras (Python)

NLP Progress for Ukrainian

- Ukrainian lemma dictionary with POS tags
  https://github.com/arysin/dict_uk
- Ukrainian lemmatizer plugin for ElasticSearch
  https://github.com/mrgambal/elasticsearch-ukrainian-lemmatizer
- **lang-uk project** (1M corpus, NER, tokenization, etc.)
  https://github.com/lang-uk

DEMO 1: EXPLORING SEMANTIC PROPERTIES OF ASOIAF (“GAME OF THRONES”)

DEMO 2: TOPIC MODELING FOR DOU.UA COMMENTS



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GitHub Repos with IPython Notebooks

- https://github.com/YuriyGuts/thrones2vec
- https://github.com/YuriyGuts/dou-topic-modeling

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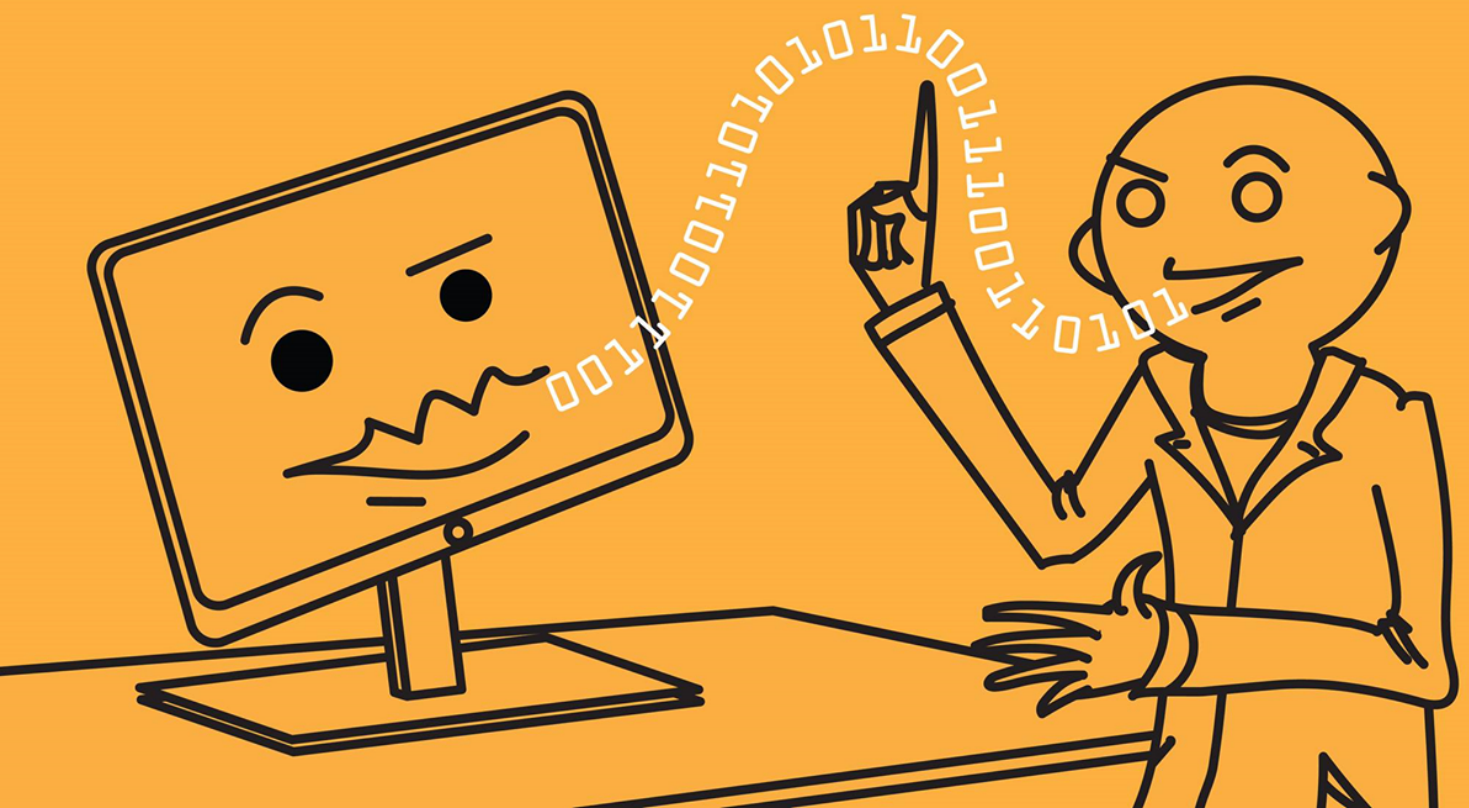

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