

Deep Learning and Machine Learning in Industry, 3 applications

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Outline

What are Machine Learning and Deep learning

Machine Learning and Machine Learning Process

Feed Forward Networks

LSTMs/CNNs

NTMs and Encoders

What is representation learning

Word2Vec

Node2vec

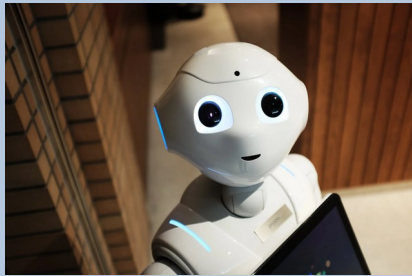
Motivating use cases

- Emotion recognition (the VERA project, Customer Management)
- HSCodes Prediction (Neural Machine Translation, Logistics)
- Representation Learning for Rule Learning (Customer Activation)

AI/Machine Learning/Deep Learning

Artificial Intelligence

Techniques mimicking human behaviour



Machine Learning

Learn from data after specifying the features

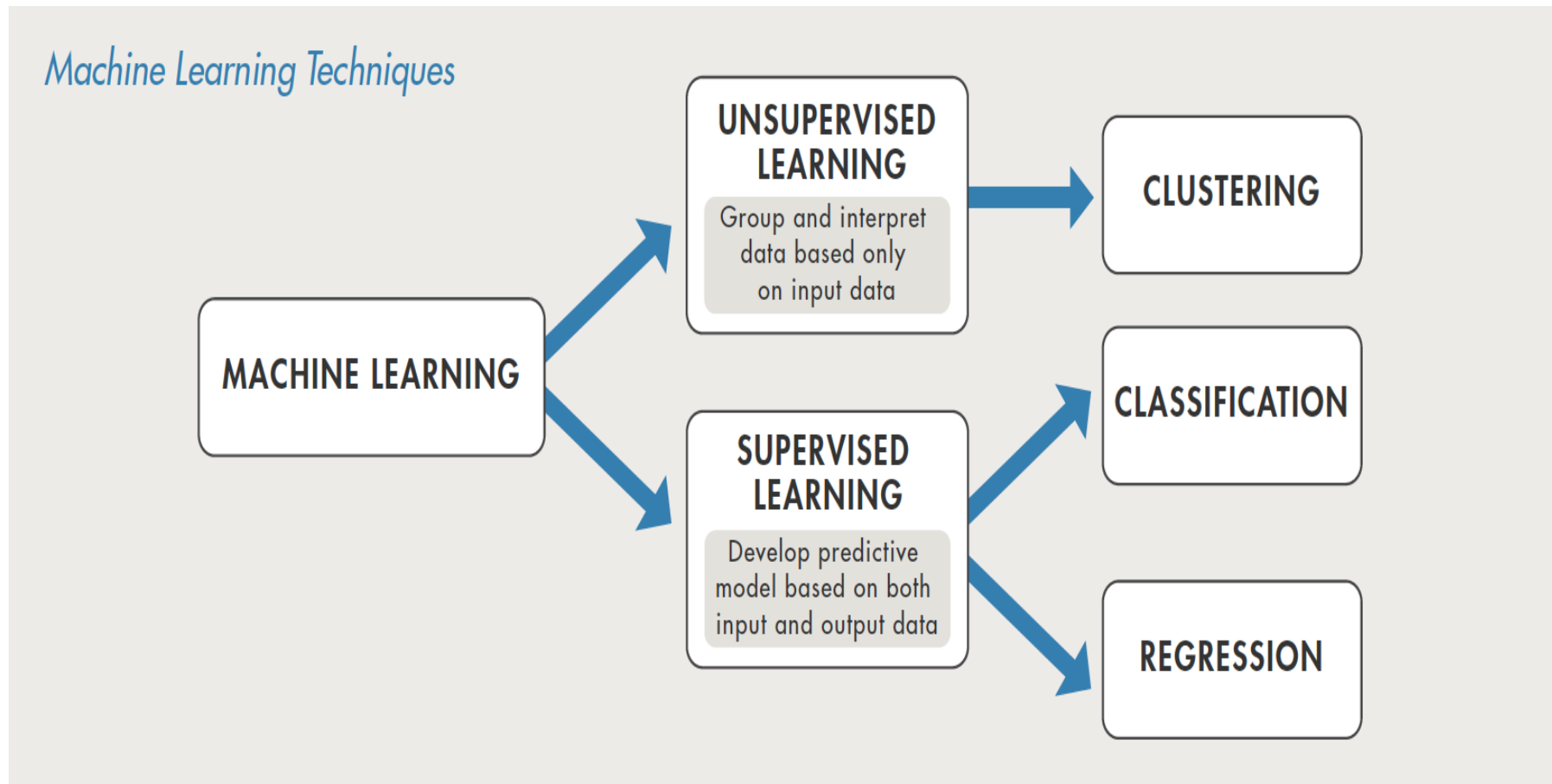


Deep Learning

Learn the features while learning from data

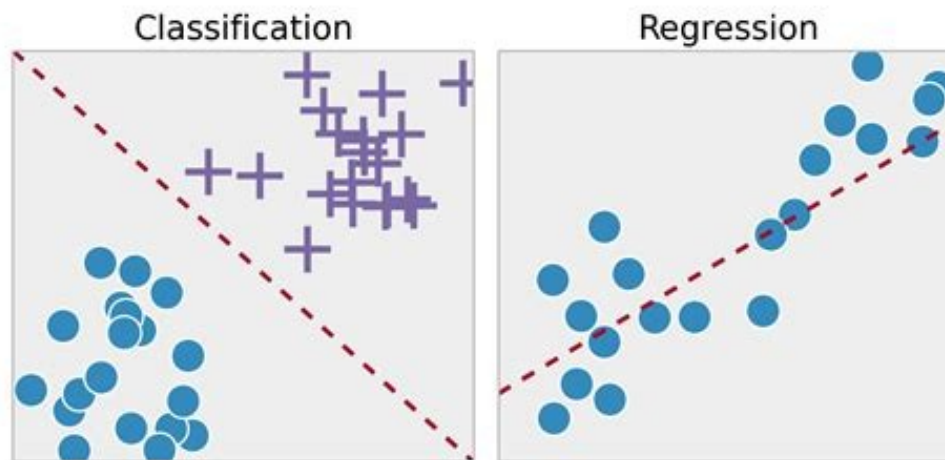


What is Machine Learning?

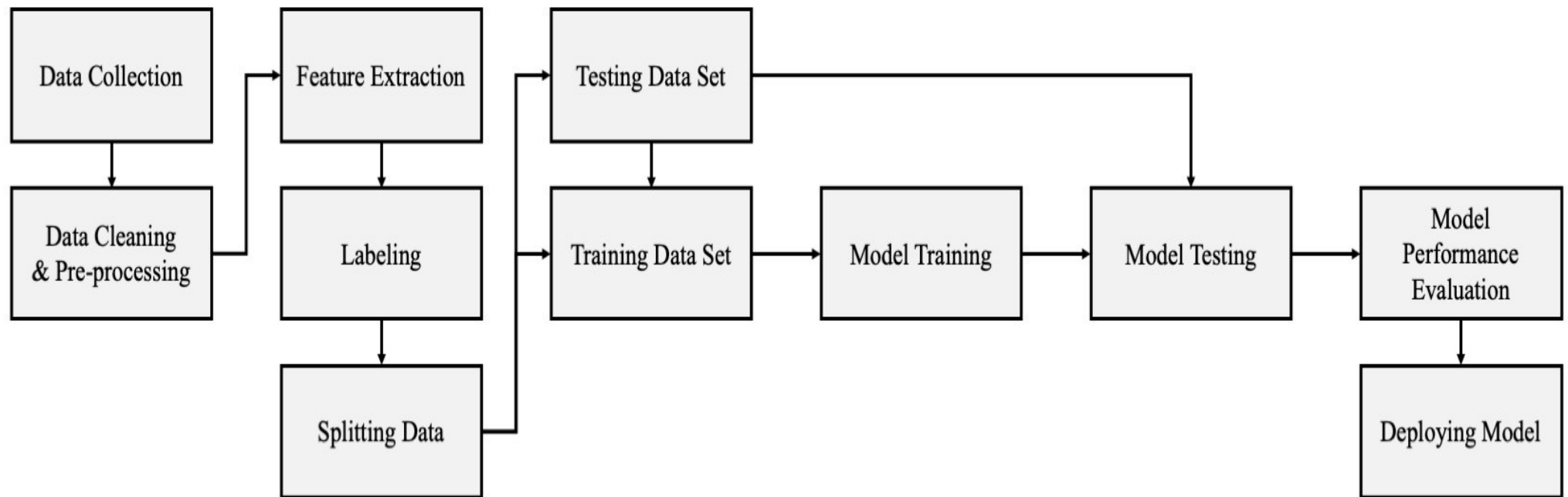


What is Machine Learning?

Machine learning trains mathematical functions to distinguish cloud of points in classes (classification) or to find a trend that fits the cloud of points (regression).



Machine Learning Process

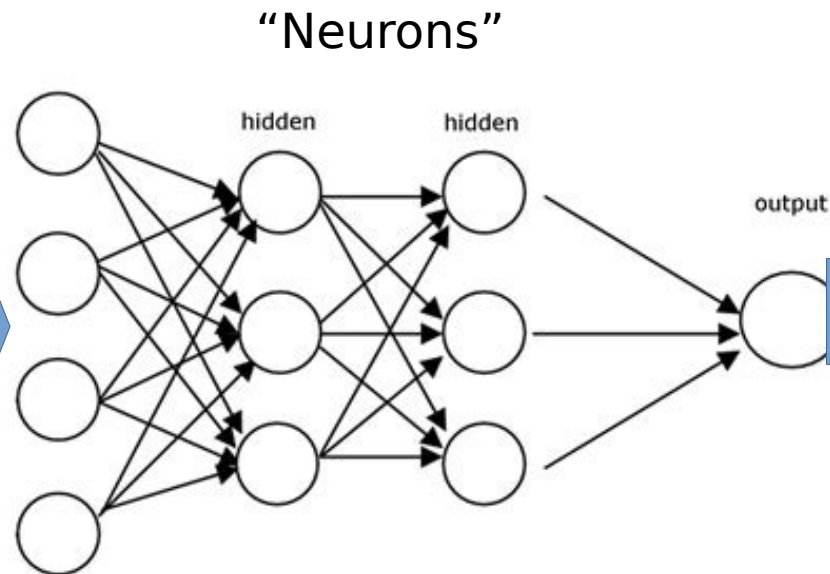


What is Deep Learning?

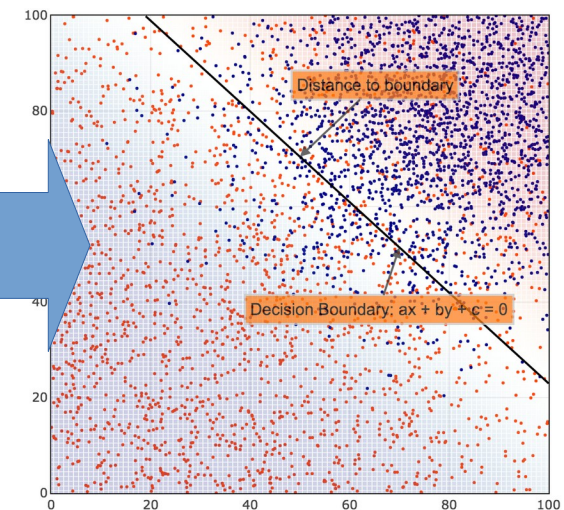
Feedforward network

Flat Data

	A	B	C	D	E	F	G	H	I	J	K
1	Full Name	Hire Date	Location	State	Termination Date	Employment Type	Year	Salary	Bonus	Overtime	Commission
2	Alison Henderson	5/13/2000	Boston	MA		FullTime	2000	\$88,000	\$6,230	\$0	
3	Corina M. Henderson	8/7/2000	Boston	MA		FullTime	2000	\$72,000	\$7,820	\$2,880	
4	Julia Hegwood	8/24/2000	Boston	MA		FullTime	2000	\$48,000	\$3,160	\$0	\$14,000
5	Jeremiah De Gracia	9/8/2000	Boston	MA		FullTime	2000	\$58,000	\$4,940	\$1,740	
6	William Nevandine	10/18/2000	Boston	MA		FullTime	2000	\$34,000	\$2,380	\$1,000	
7	Martie Elmision	11/7/2000	Boston	MA		FullTime	2000	\$54,000	\$6,480	\$2,180	
8	Alison Johnson	5/13/2000	Boston	MA		FullTime	2000	\$82,000	\$7,360	\$0	
9	Corina M. Henderson	8/7/2000	Boston	MA		FullTime	2001	\$75,000	\$5,550	\$3,750	
10	Julia Hegwood	8/24/2000	Boston	MA		FullTime	2001	\$48,000	\$2,880	\$0	\$44,000
11	Jeremiah De Gracia	9/8/2000	Boston	MA		FullTime	2001	\$62,000	\$3,100	\$3,100	
12	William Nevandine	10/18/2000	Boston	MA		FullTime	2001	\$34,000	\$2,520	\$1,080	
13	Martie Elmision	11/7/2000	Boston	MA		FullTime	2001	\$60,000	\$4,200	\$2,400	
14	Kelly Queen	1/13/2001	Los Angeles	CA		FullTime	2001	\$43,000	\$3,160	\$0	\$42,000
15	Cristian Roth	4/2/2001	Los Angeles	CA		FullTime	2001	\$54,000	\$4,320	\$0	
16	Jeanne Melendez	6/4/2001	Los Angeles	CA		FullTime	2001	\$32,000	\$2,560	\$0	
17	Brian M. Busci	5/10/2001	Chicago	IL		FullTime	2001	\$43,000	\$3,440	\$0	\$22,000
18	Cheryl Summerville	6/29/2001	Chicago	IL		FullTime	2001	\$43,000	\$3,780	\$0	
19	Tony Merisich	9/18/2001	Chicago	IL		FullTime	2001	\$126,000	\$9,450	\$3,150	
20	Wayne Anderson	10/4/2001	Chicago	IL		FullTime	2001	\$44,000	\$3,960	\$3,000	
21	Isabella Restrepo	10/11/2001	Boston	MA		FullTime	2001	\$18,000	\$1,680	\$0	\$18,000

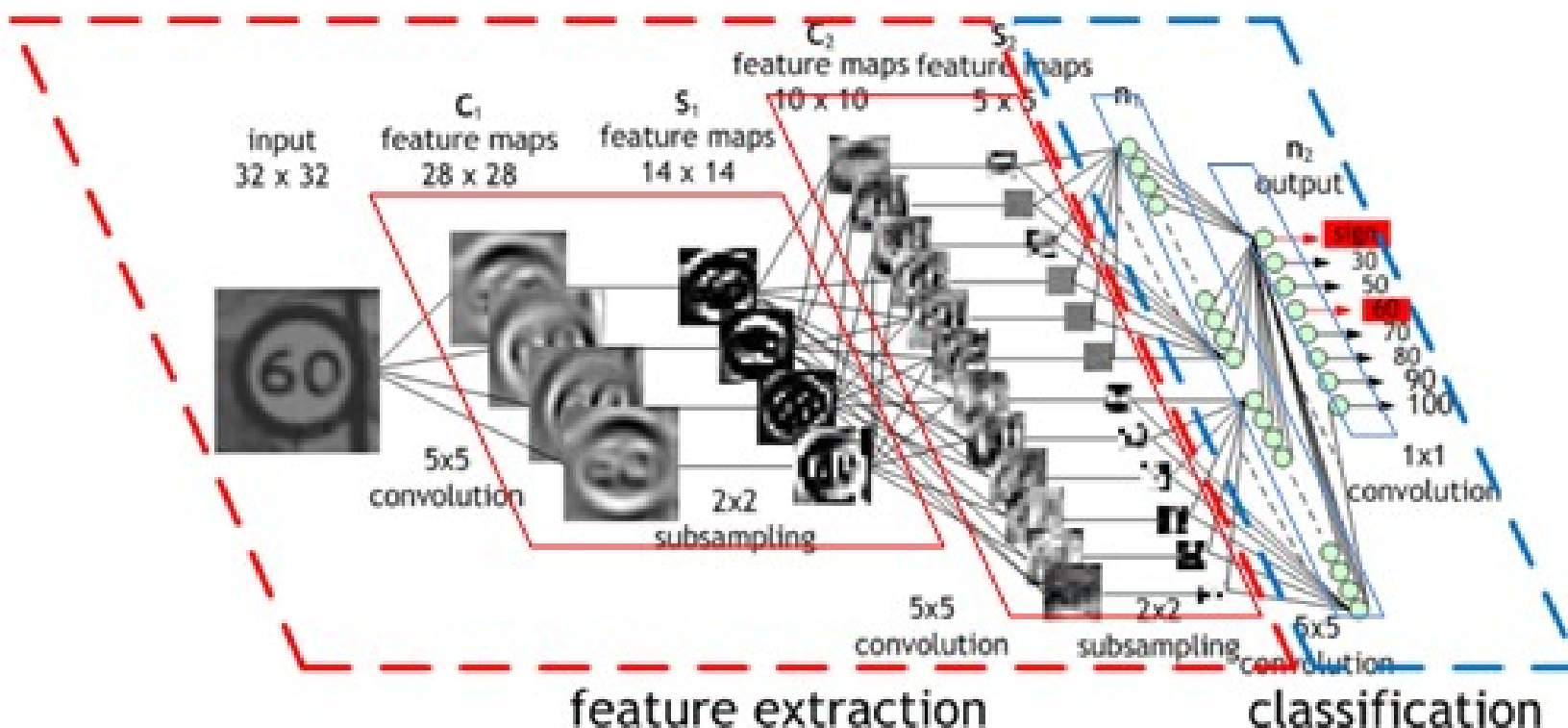


Equation of classification boundary



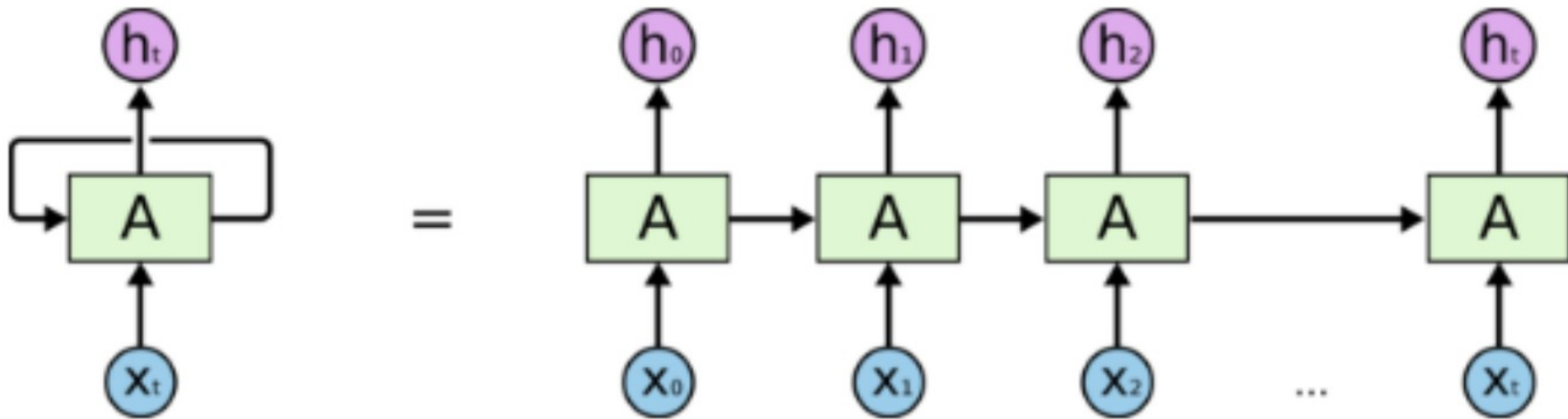
What is Deep Learning?

Convolutional Network (for images)



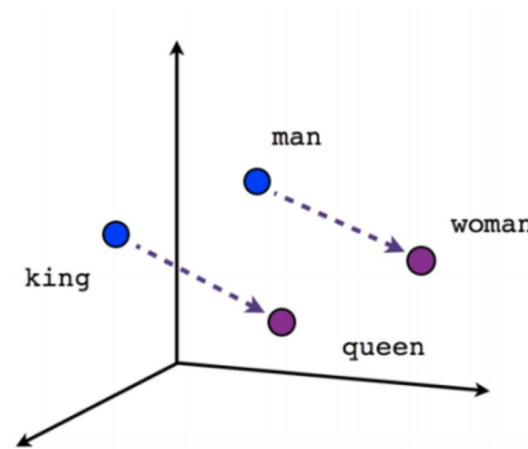
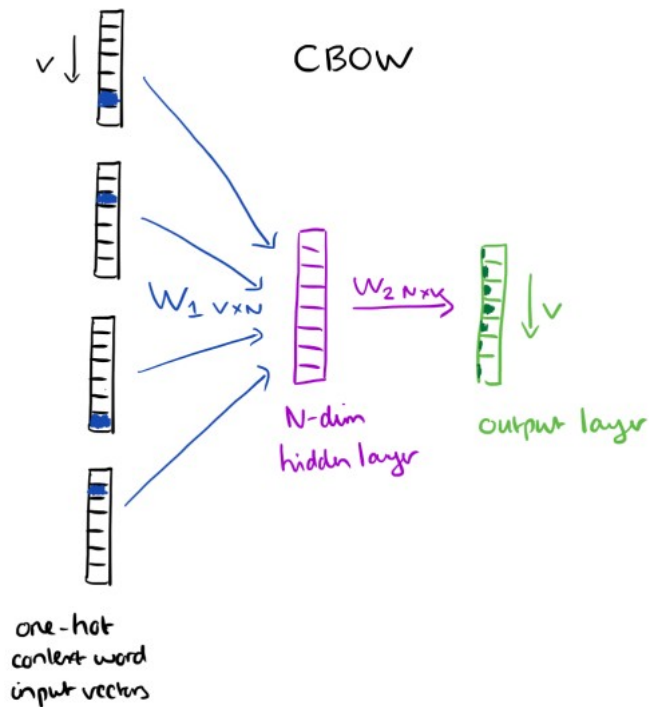
What is Deep Learning?

LSTM Network (for sequences)

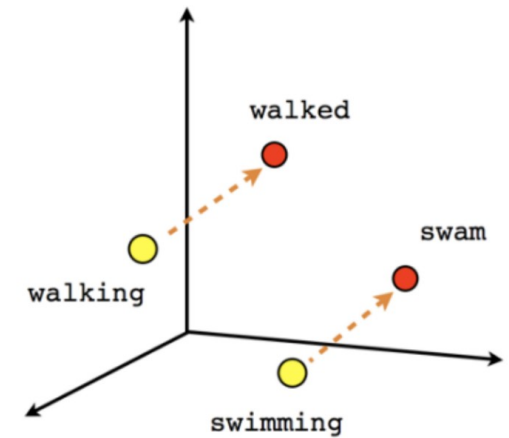


An unrolled recurrent neural network.

Representation Learning, Word2Vec

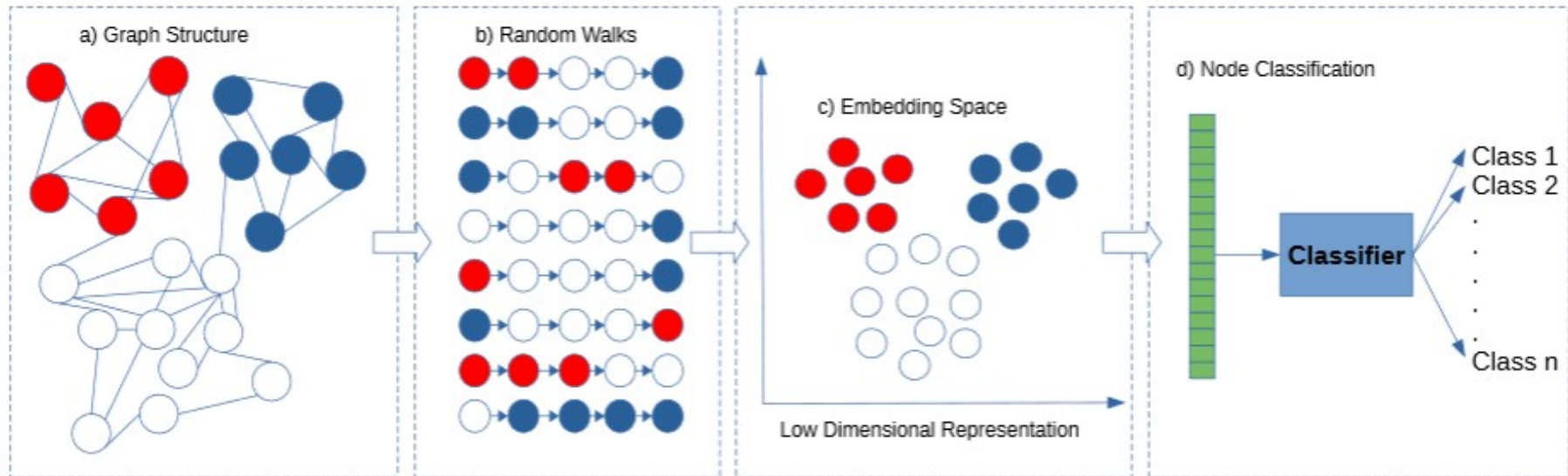


Male-Female



Verb tense

Representation Learning, Node2Vec



Motivating Use Cases

3 Applications from Industry:

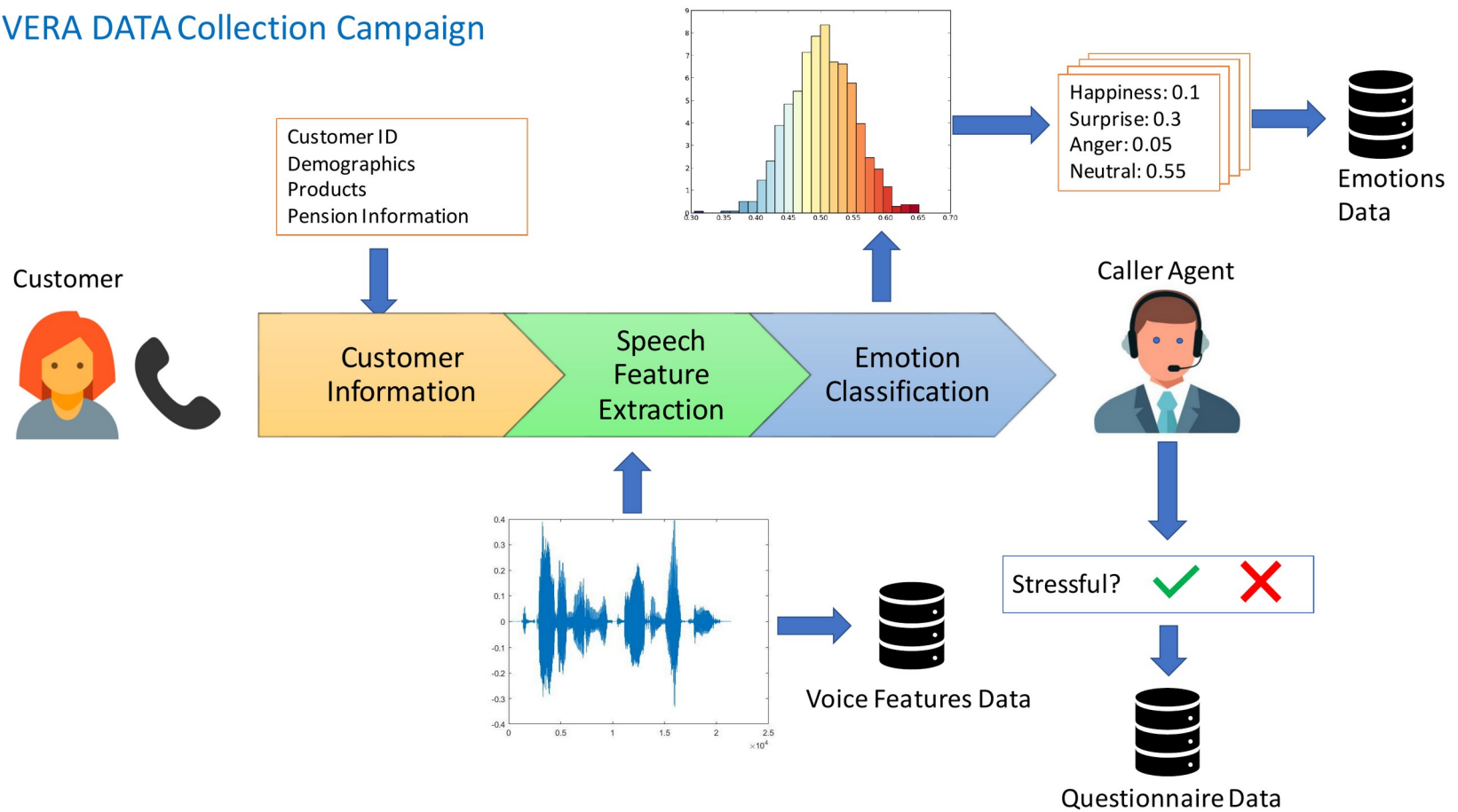
Emotion recognition (the VERA project, Customer Management)

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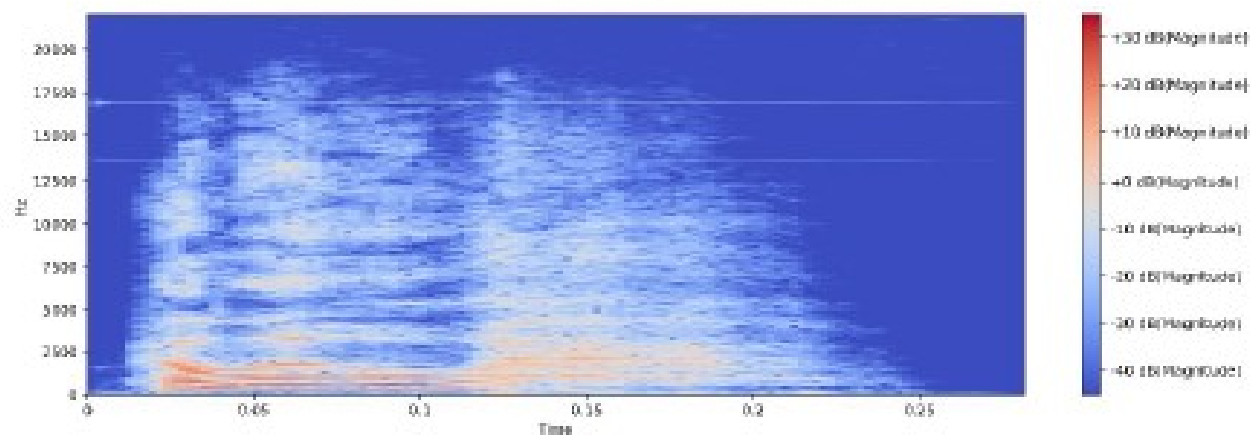
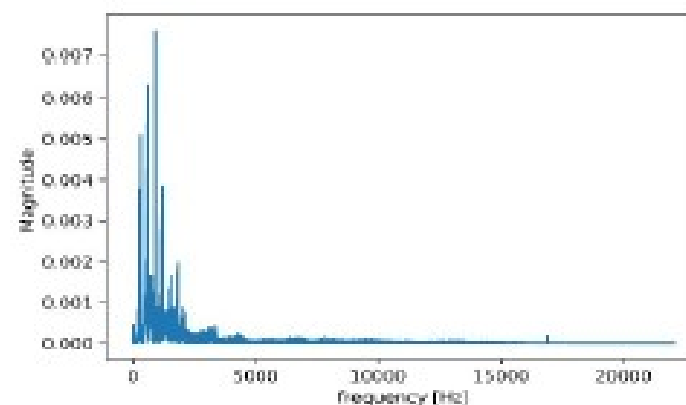
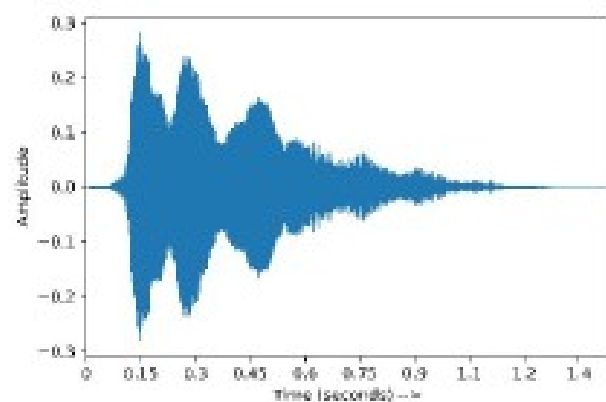
Motivating Use Cases: VERA

VERA DATA Collection Campaign

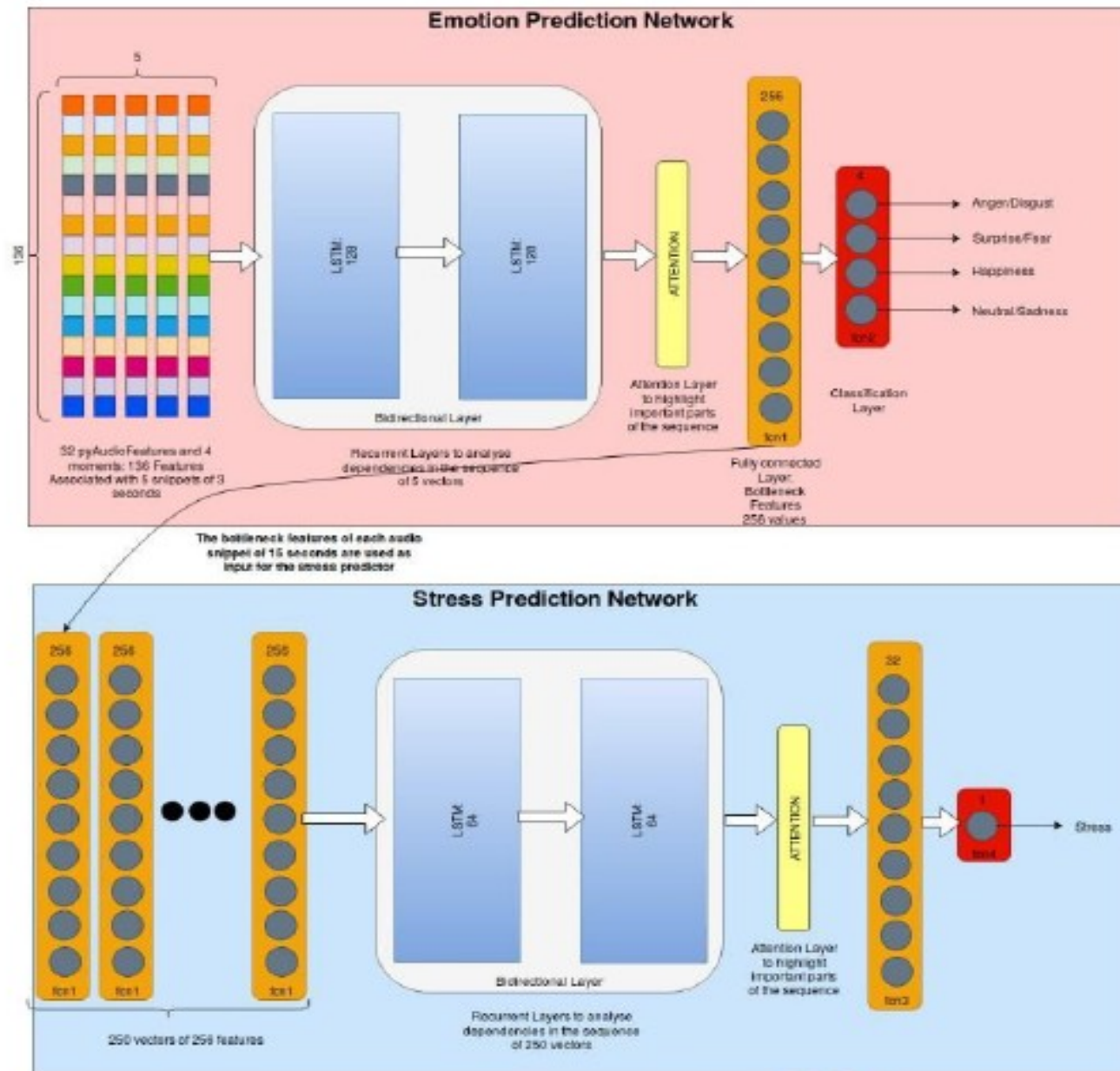


VERA Voice Signal

A2. Time-frequency representations of a voice signal



VERA Architecture



Results: Emotion and Stress Prediction

	<u>1DLA</u>			<u>LA</u>			<u>BIL</u>			<u>Frequency Classifier</u>		
	<i>Prec.</i>	<i>Recall</i>	<i>f1</i>	<i>Prec.</i>	<i>Recall</i>	<i>f1</i>	<i>Prec.</i>	<i>Recall</i>	<i>f1</i>	<i>Prec.</i>	<i>Recall</i>	<i>f1</i>
Anger /	0.21	0.12	0.17	0.21	0.17	0.19	0.27	0.18	0.22	0.08	0.09	0.08
Disgust	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Fear /	0.23	0.25	0.19	0.19	0.19	0.19	0.21	0.21	0.21	0.12	0.15	0.13
Surprise	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Happiness	0.25	0.07	0.1	0.24	0.26	0.27	0.28	0.17	0.21	0.1	0.09	0.09
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Sadness /	0.78	0.88	0.83	0.8	0.81	0.81	0.8	0.86	0.83	0.73	0.68	0.71
Neutral	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Micro Avg.	0.67	0.67	0.67	0.68	0.68	0.68	0.68	0.68	0.68	0.53	0.53	0.53
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Note. The upper statistic represents the mean and the lower statistic in-between brackets represents the 95%-confidence interval ($p < .05$).

Table 4. Stress prediction network performance.

Stress network predictor	Precision	Recall	f1-score
No-stress	0.86 (0.03)	0.84 (0.03)	0.85 (0.03)
Stress	0.68 (0.06)	0.7 (0.06)	0.69 (0.06)
Micro-avg	0.8 (0.03)	0.8 (0.03)	0.8 (0.03)

Note. The upper statistic represents the mean and the lower statistic in-between brackets represents the 95%-confidence interval ($p < .05$).

VERA: Ethical Problems

- **Usage of emotions patterns to scam people into doing something**
- **Usage of emotion patterns to lure information**
- **Usage of emotion patterns to fire personnel**
- **Profiling and tracking people based on emotion responses**

Motivating Use Cases: HS Codes

HS Code Example

Apple

HS Code: 08081000



International

National

08 08 10 00 00 00

Section 02: Vegetable Products

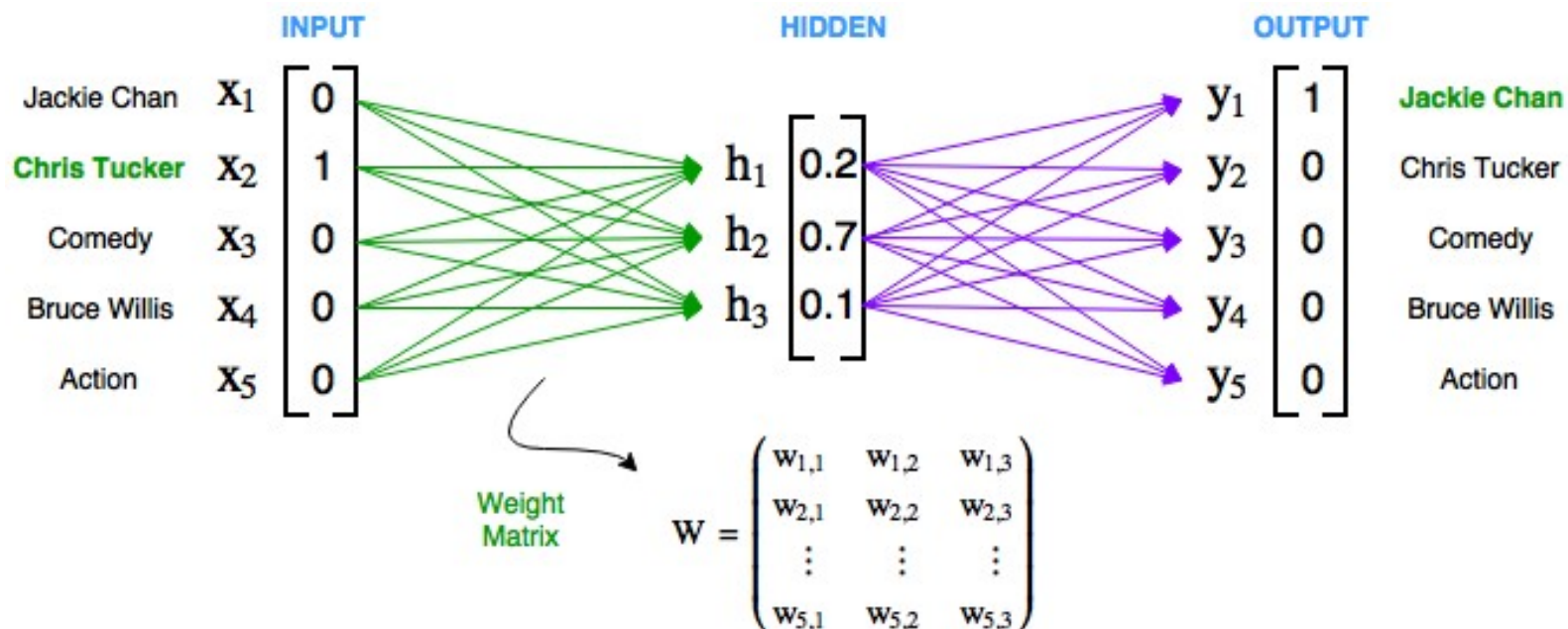
Chapter 08: Edible Fruit and nuts, peel of citrus/melons

Heading 08: Apples, Pears and Quinces, Fresh

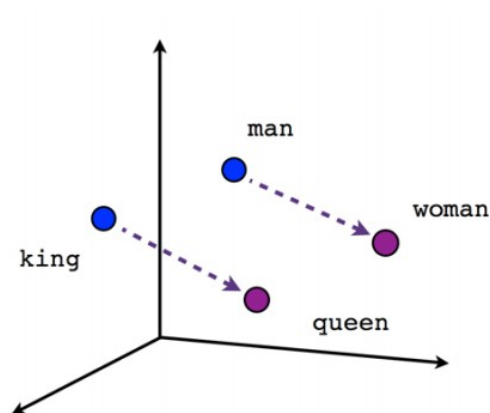
Subheading 10: Apples

Country Specific Divisions

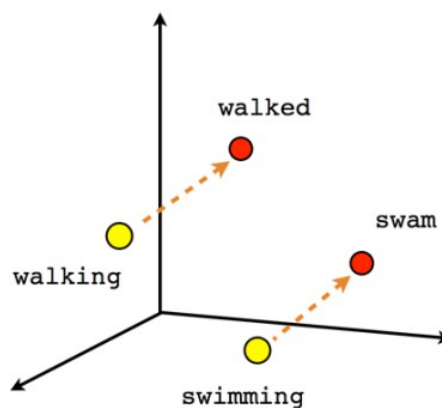
Component 1: Word Embeddings



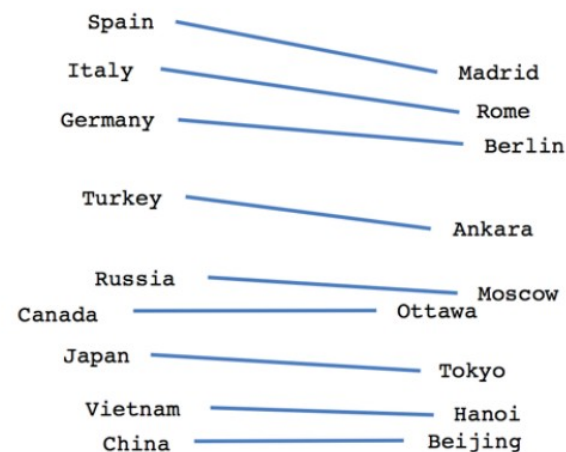
Component 1: Word Embeddings



Male-Female

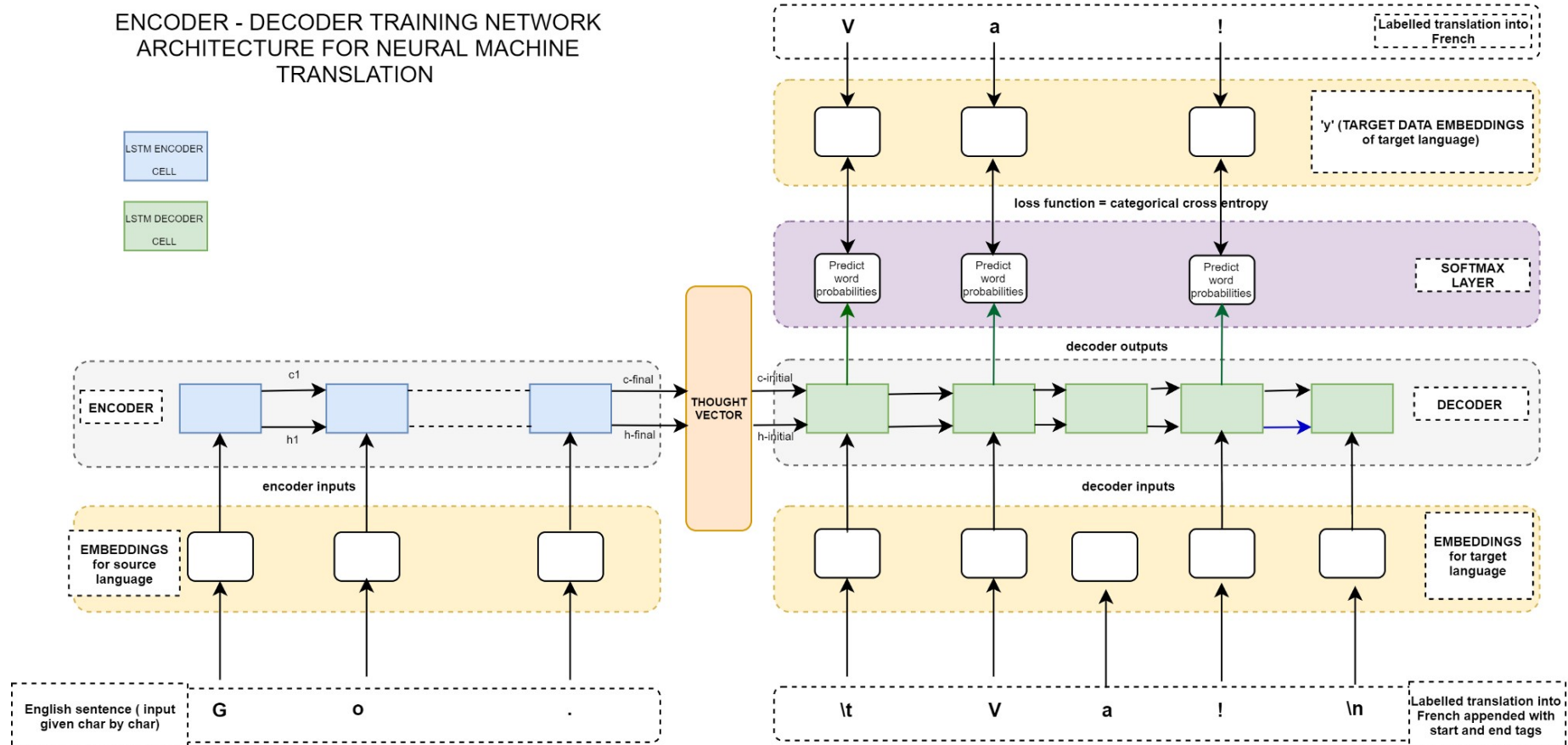


Verb tense

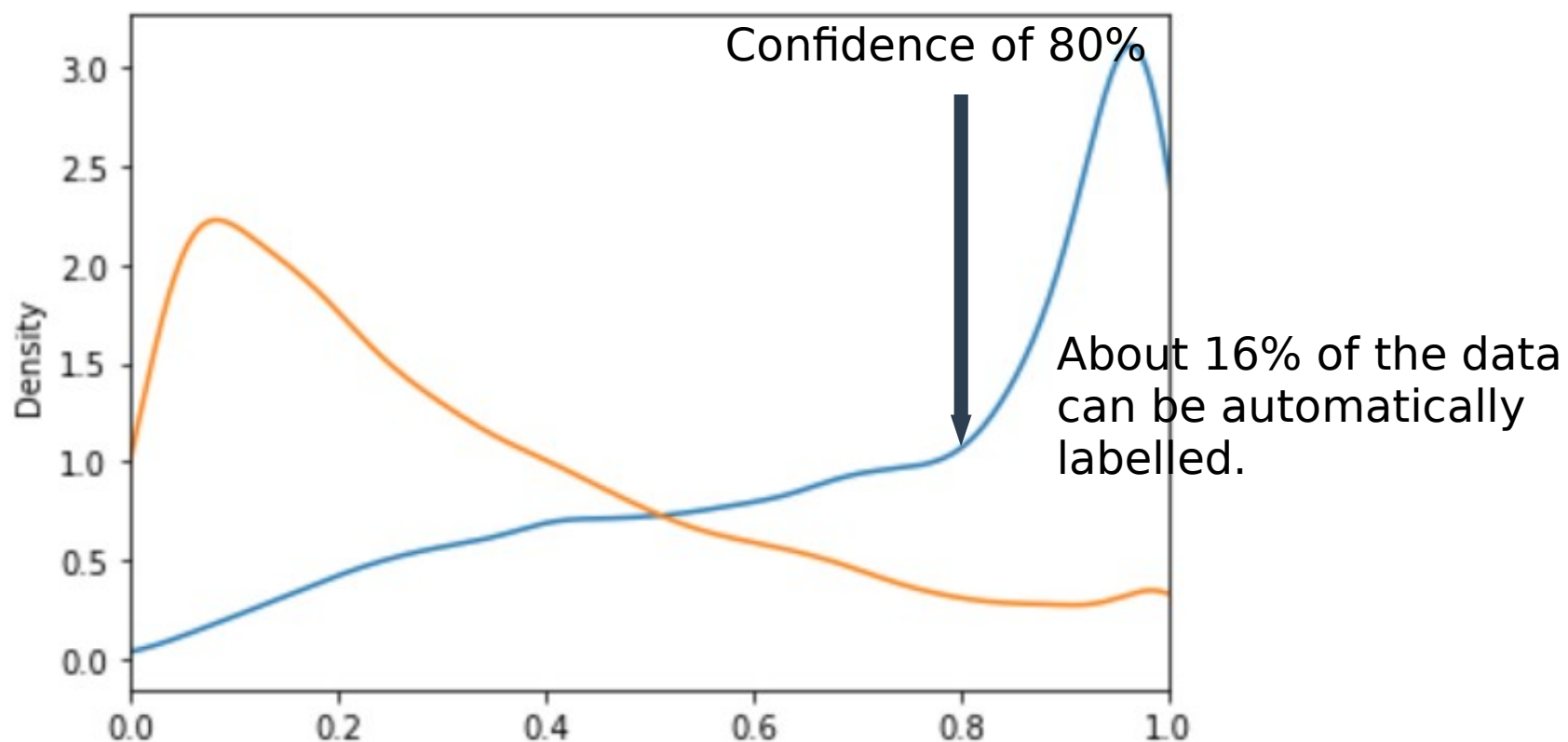


Country-Capital

Component 2: Neural Machine Translator



Quality Curves



Results

- **The NMT succeeds at classifying about 16% of the data with a 80% confidence.**
- **This result is going to be replicated through 11 states (the biggest ones being Germany and UK)**
- **Any percentage point of saving is tens of thousands of euros.**

HS Codes: Ethical Problems

The main issue with **automating** everything is that less people will be hired to perform the job that the robot is taking care of.

Of course the same people could be used for something more **meaningful** if the process is particularly repetitive.

Profiling is also a problem, although less accentuated in this particular case, given that a code has to be provided by **law**.

Motivating Use Case, Segmenting Customers for Customer Activation

Pension funds send news letters to:

Advise the customer concerning their pension

Changes in the law

Notify a new available service

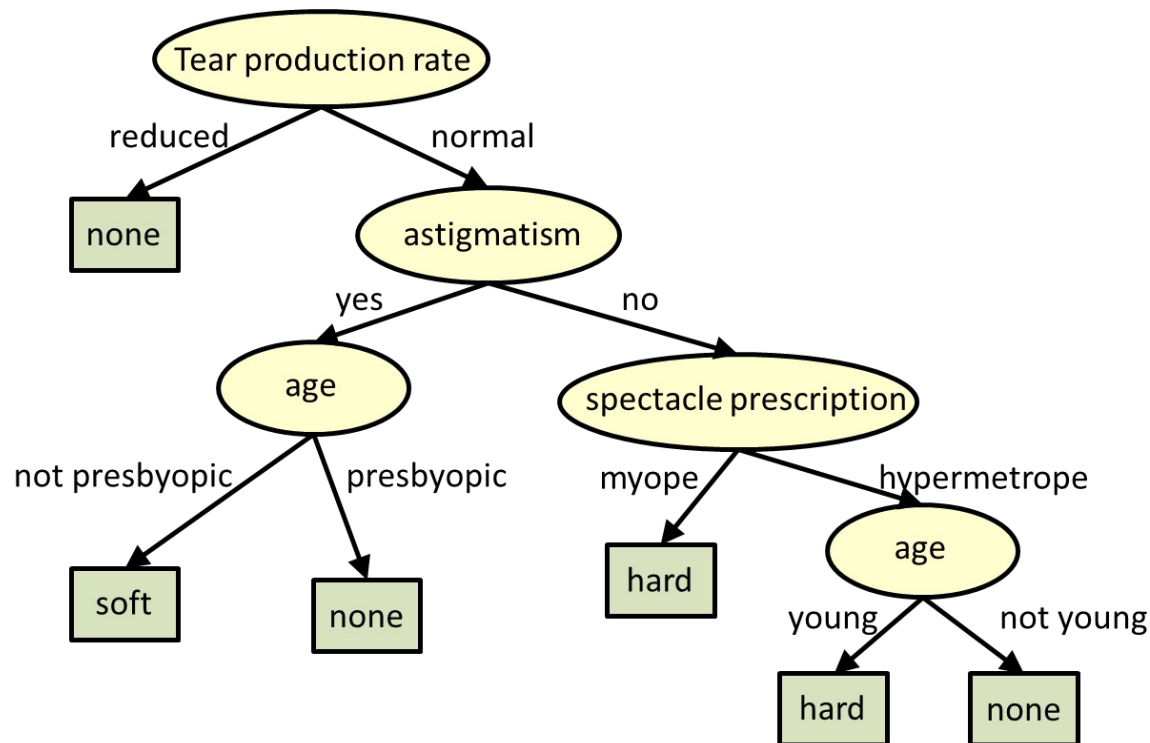
Notify changes in the taxation

The pension fund really needs that as many customers as possible check the information, but the budget is limited!

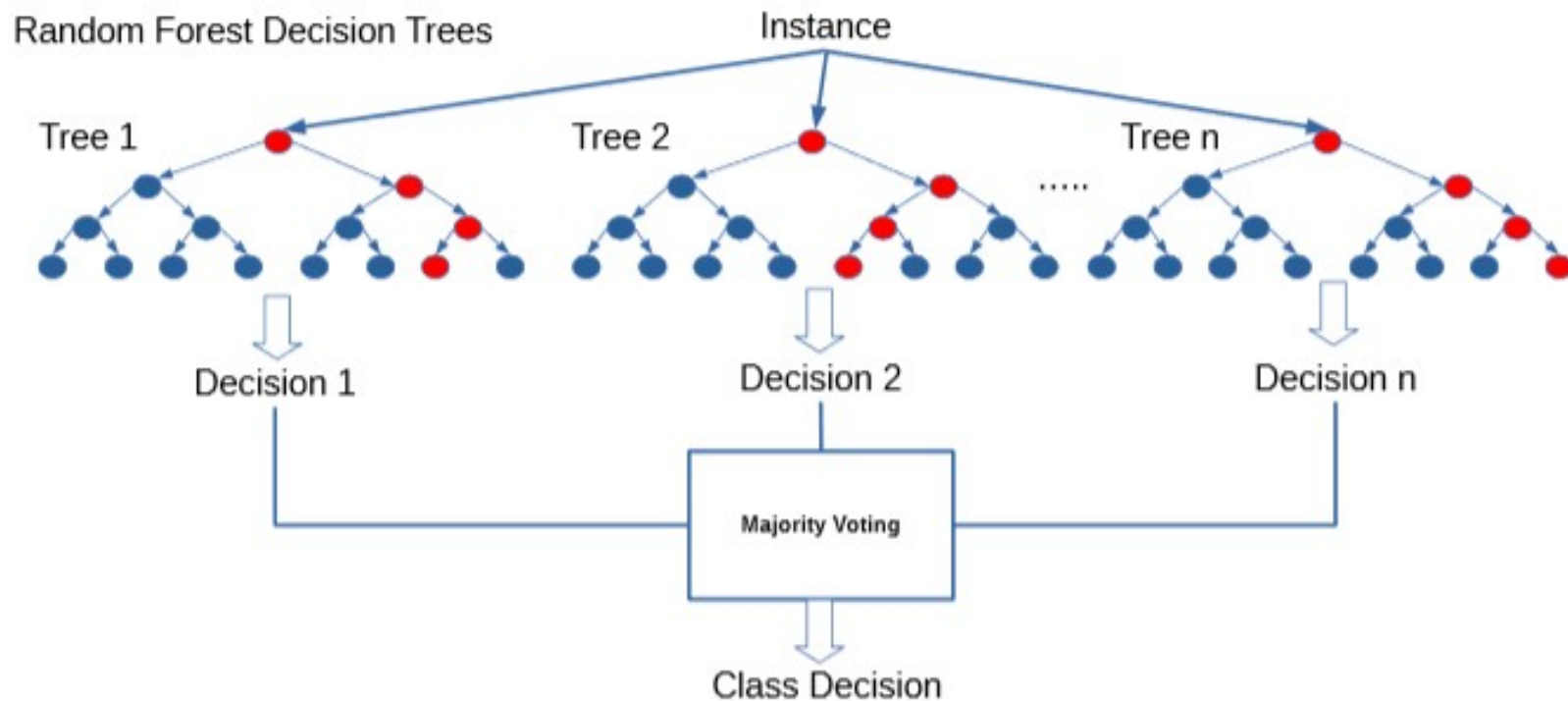
→ **Machine Learning to segment the customers!**

The problem: Machine learning algorithms are black boxes (?)

Not always, Decision trees are not black box. They define rules.

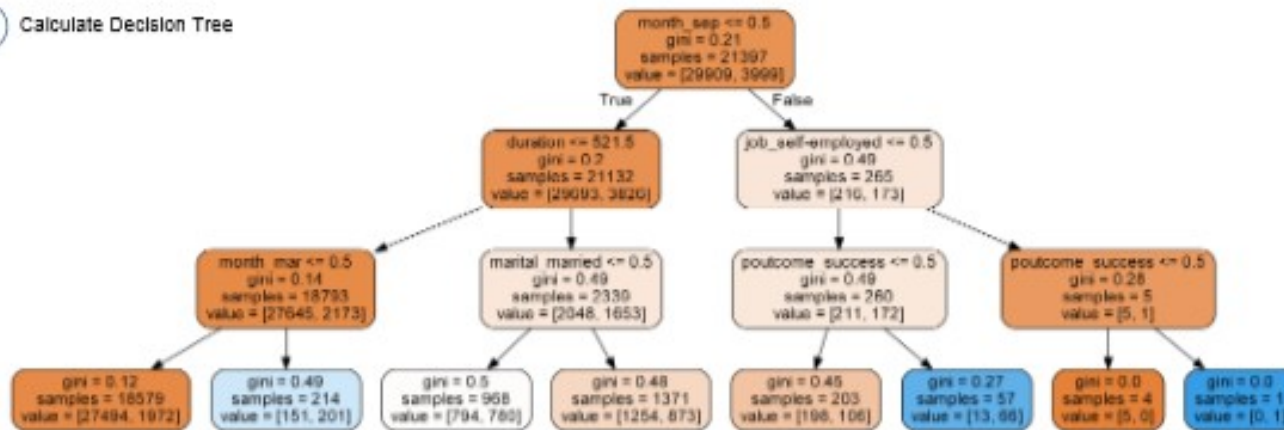


Motivating Use Cases: Random Forest Node Embeddings

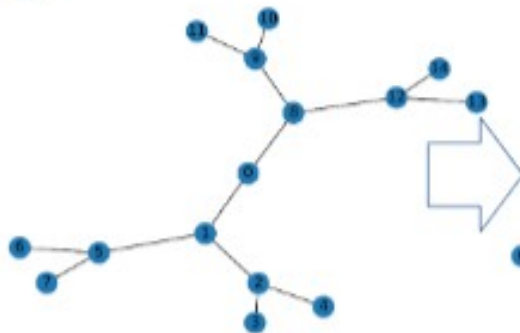


Random Forest Node Embeddings Example

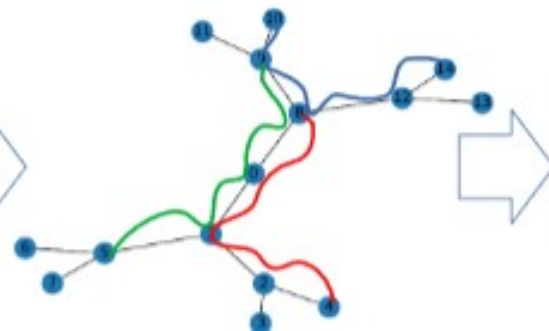
1 Calculate Decision Tree



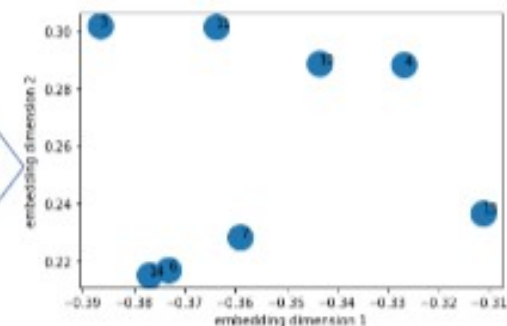
2 Calculate Tree



3 Node2Vec Random Walks



4 Calculate Node Embeddings

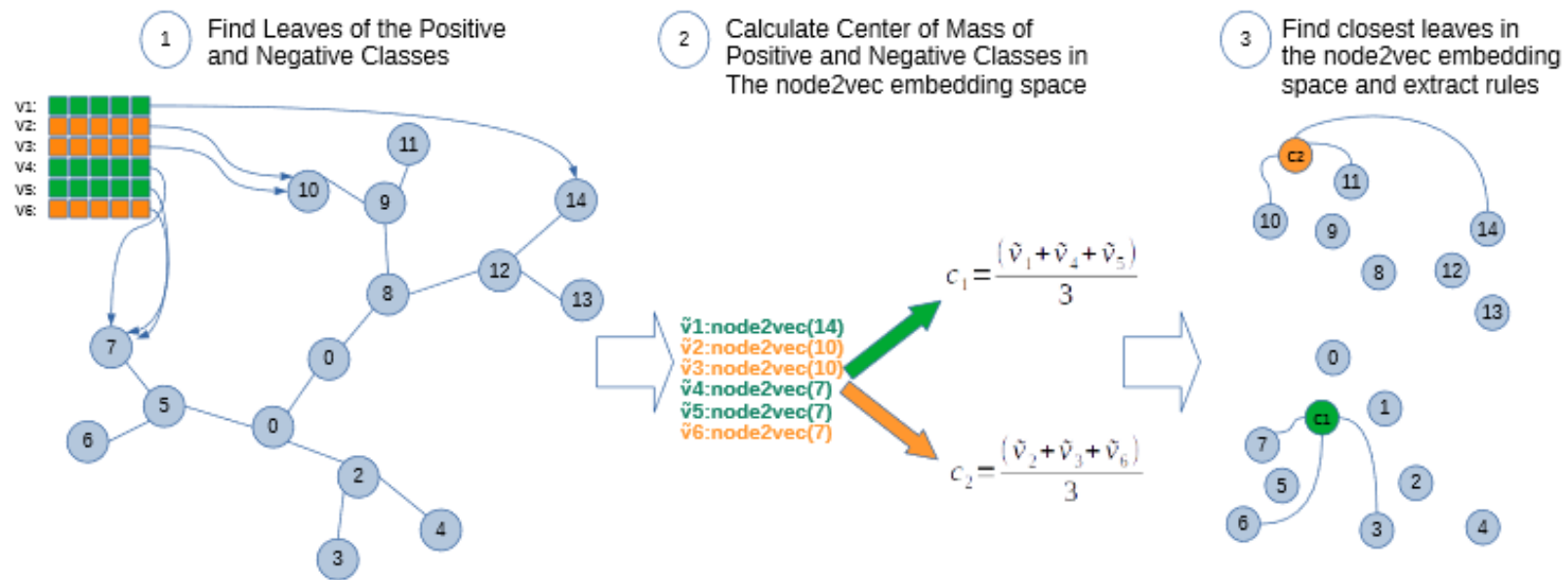


RFNE Some Results, classify

Method	D1	D2	D3	D4
KNN	0.849	0.533	0.566	0.931
Naive Bayes	0.0729	0.568	0.615	0.90
Logistic Regression	0.861	0.608	0.641	0.941
RandomForest	0.922	0.657	0.707	0.947
ExtraTrees	0.920	0.624	0.686	0.945
Random Forest Node Embeddings	0.907	0.657	0.722	0.948

It does not lose information wrt RandomForests,
so it is a plausible feature extraction

RFNE, Describe



RFNE, Describe

	log odds	stde	z	P> z	[0.025	0.975]	odds
Intercept	-4.0580	0.186	-21.846	0.000	-4.422	-3.694	0.017284
feature_0	0.2344	0.134	1.751	0.080	-0.028	0.497	1.264150
feature_1	0.2812	0.078	3.620	0.000	0.129	0.433	1.324719
feature_2	0.3986	0.067	5.967	0.000	0.268	0.530	1.489738
feature_3	0.7227	0.098	7.346	0.000	0.530	0.916	2.059988
feature_4	-0.2204	0.069	-3.201	0.001	-0.355	-0.085	0.802198
feature_5	0.0864	0.093	0.924	0.355	-0.097	0.270	1.090242
feature_6	-0.1506	0.108	-1.392	0.164	-0.362	0.061	0.860192
feature_7	-0.0289	0.076	-0.378	0.706	-0.179	0.121	0.971514
feature_8	-0.1441	0.098	-1.473	0.141	-0.336	0.048	0.865801
feature_9	0.6914	0.096	7.192	0.000	0.503	0.880	1.996509
feature_10	-0.2434	0.133	-1.824	0.068	-0.505	0.018	0.783958

$rule_{d1} = \text{pdays} < 9.5 \text{ and marital} \neq \text{'single' and}$
 $\text{job} \in [\text{"admin."}, \text{"blue-collar"}, \text{"entrepreneur"}, \text{"housemaid"}] \text{ and}$
 $\text{age} < 61.5 \text{ and day} > 18.5$

Ethical Problems

- **Segmenting Customers to hypertarget them with the perfect advertisement.**
- **Scamming customers very effectively and cheaply.**
- **Grouping Customers unfairly, without their consent.**

Conclusion

- **AI offers many advantages**
 - Automation
 - Targeting population
 - Produce New insights
- **It comes with a number of negative aspects:**
 - People lose jobs
 - Scamming
 - Unfair use of data
 - Intellectual property

Questions ?

