

When DevOps meets Machine Learning How DevOps can help Machine Learning

steve.ross-talbot@estafet.com







Estafet

- Founded in 2002
- Specialist integration and data insight consultancy
- Distributed Agile Delivery
- Mix of 80 developers and consultants in UK and Sofia, Bulgaria
- Industry experience includes finance, utilities, retail, manufacturing
- We are known for "Engineering Excellence"



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Efficiency
 Effectiveness

f Costs

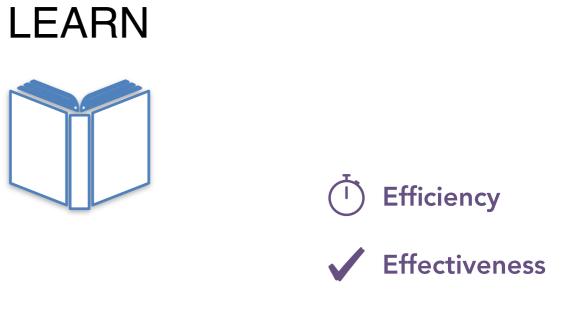












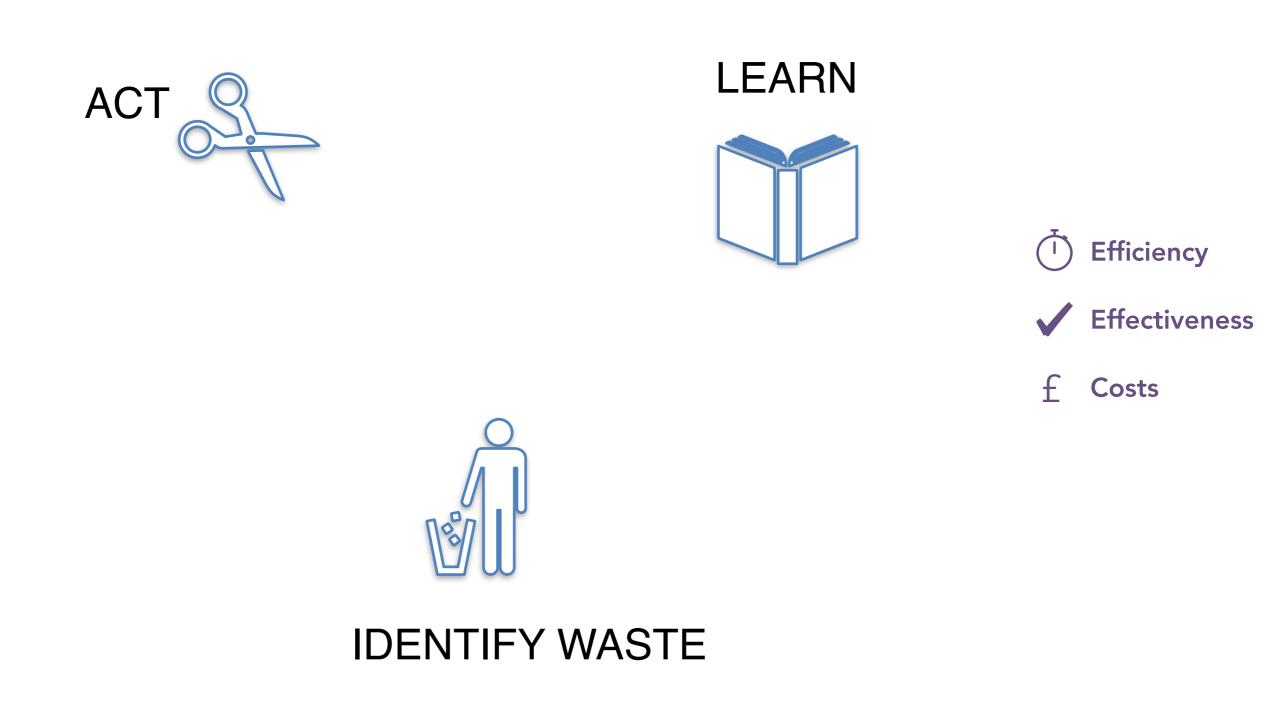




IDENTIFY WASTE









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- To deliver stories ready to be deployed into production each and every sprint
- To continuously deliver into production (eventually up to several deliveries each day)



LEARN

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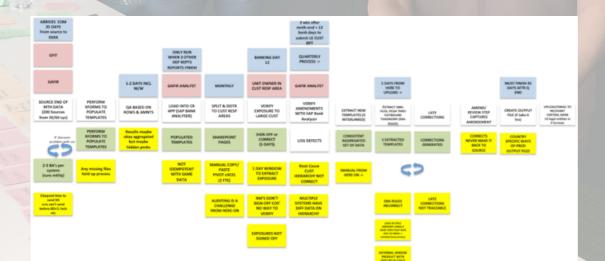
 To deliver stories ready to be deployed into production each and every sprint

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LEARN

- To deliver stories ready to be deployed into production each and every sprint
- To continuously deliver into production (eventually up to several deliveries each day)



Time scale

Actor

Activity

Artefact

Pain Point

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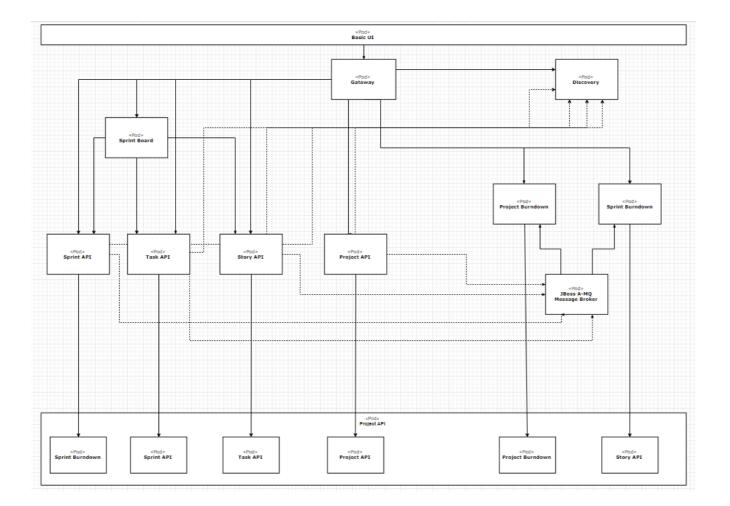
- Remove friction from the delivery process by automating what we can
- Incorporate monitoring and tracing tools into the delivery process
- Reduce rework in the form of defects caused by environmental and configuration drift

 Detect and address issues as soon as they occur www.estafet.com



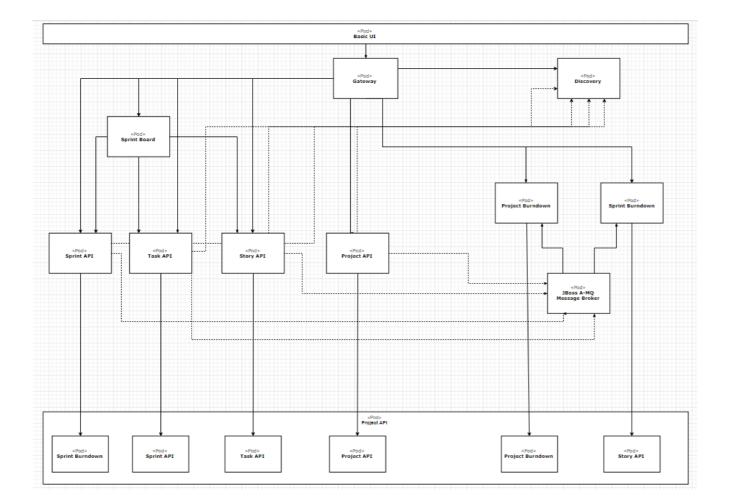


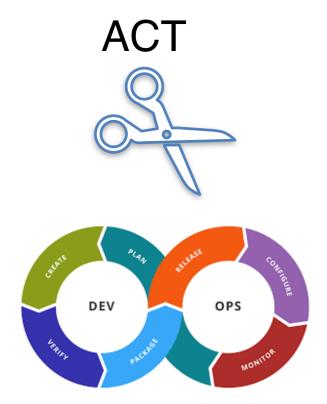






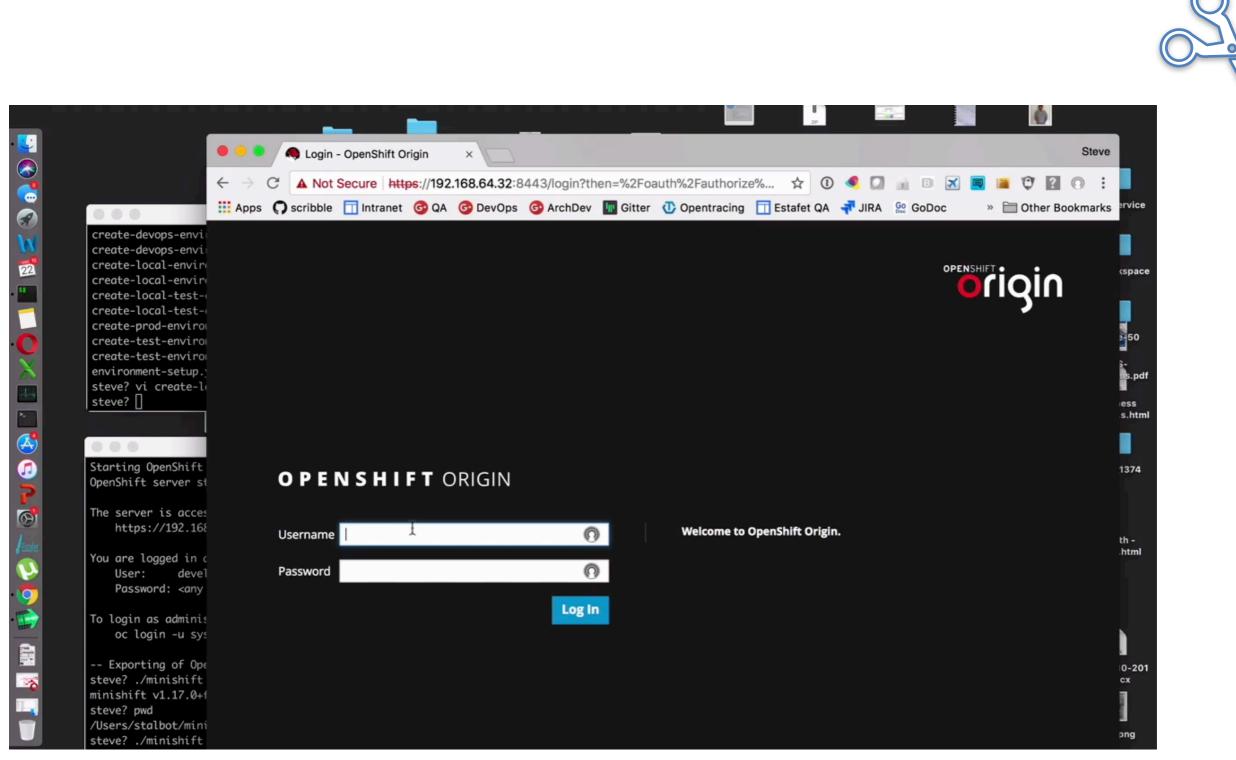






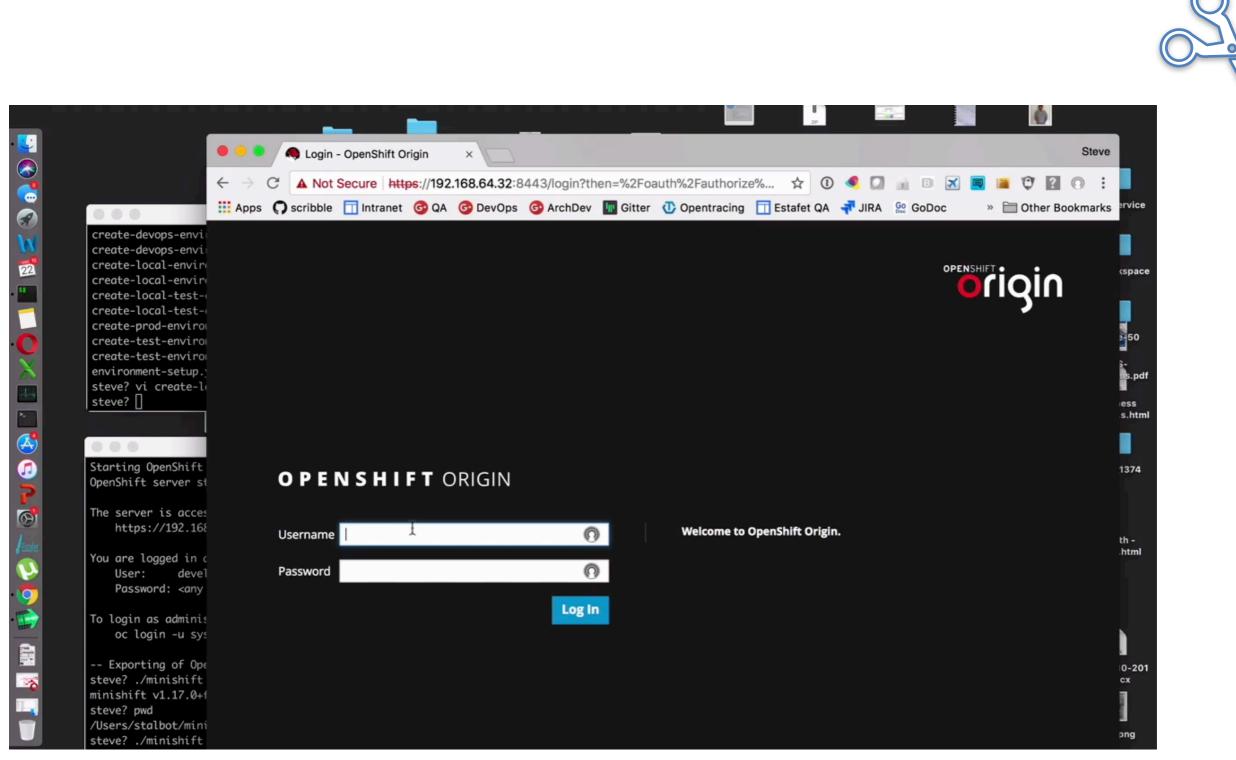


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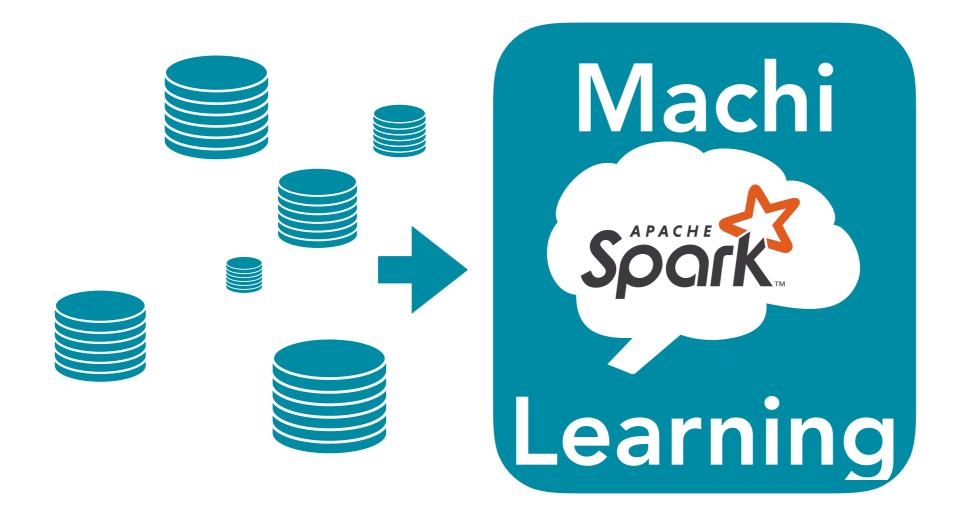


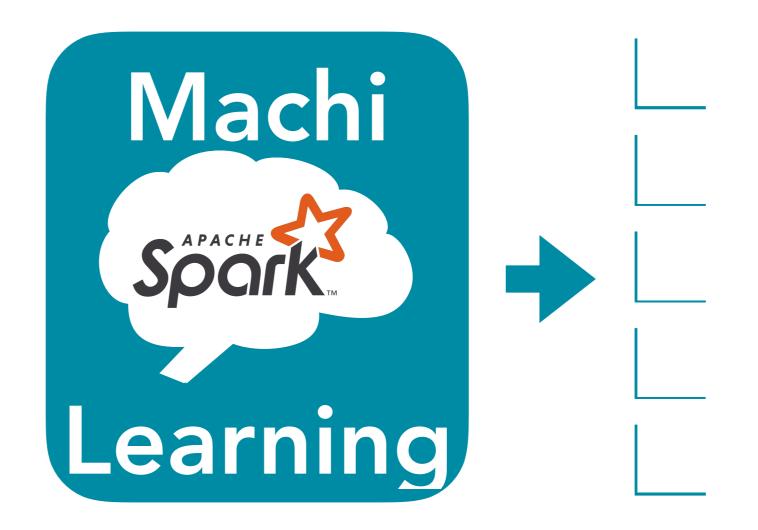


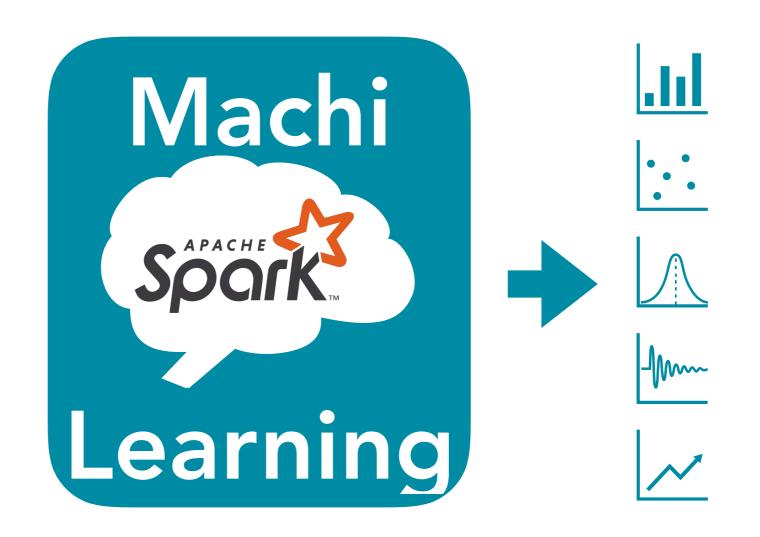
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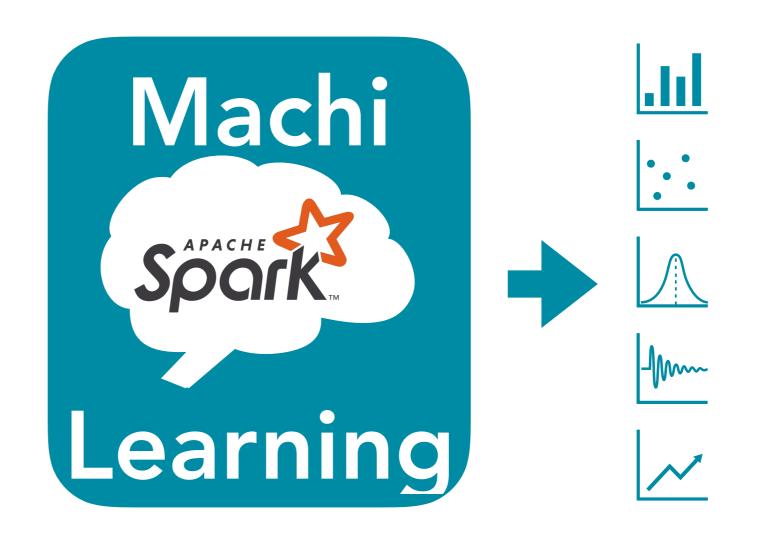












1. Understand your data

2. It requires preprocessing

3. There's a lot of experimentation

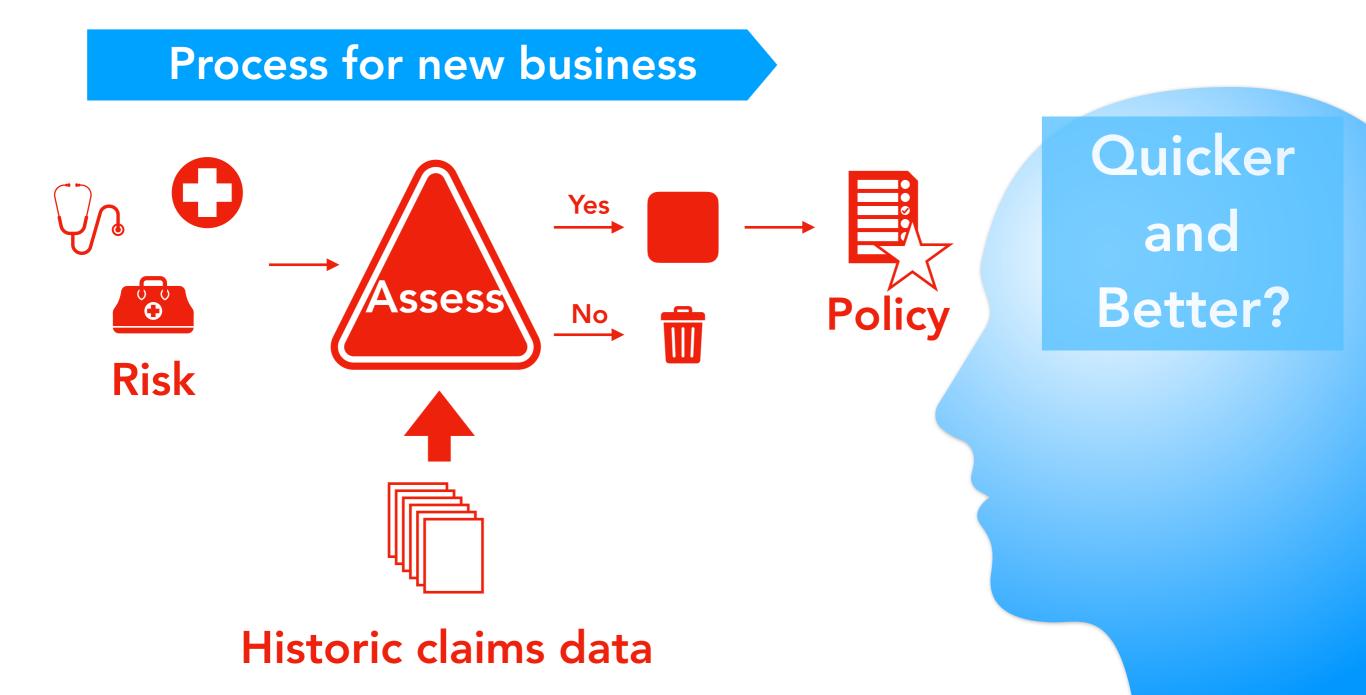
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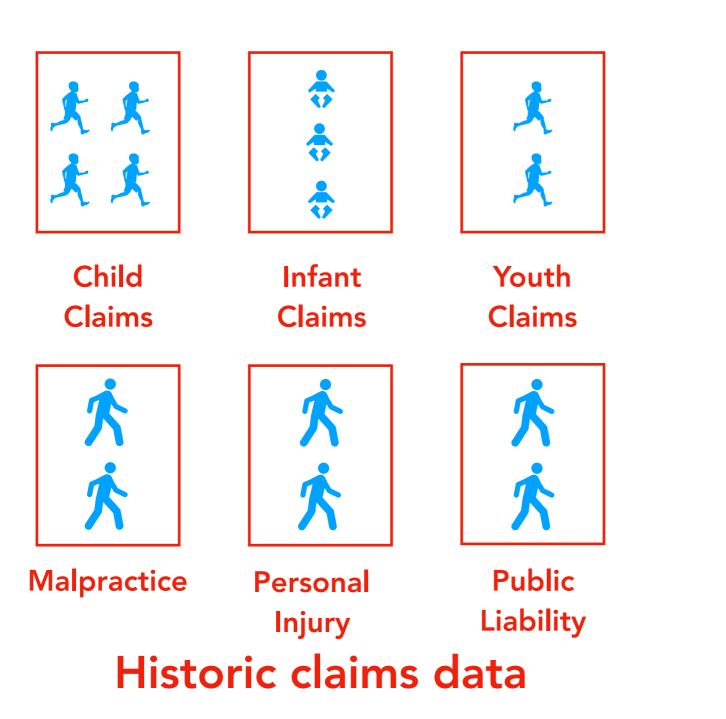
2. It requires preprocessing

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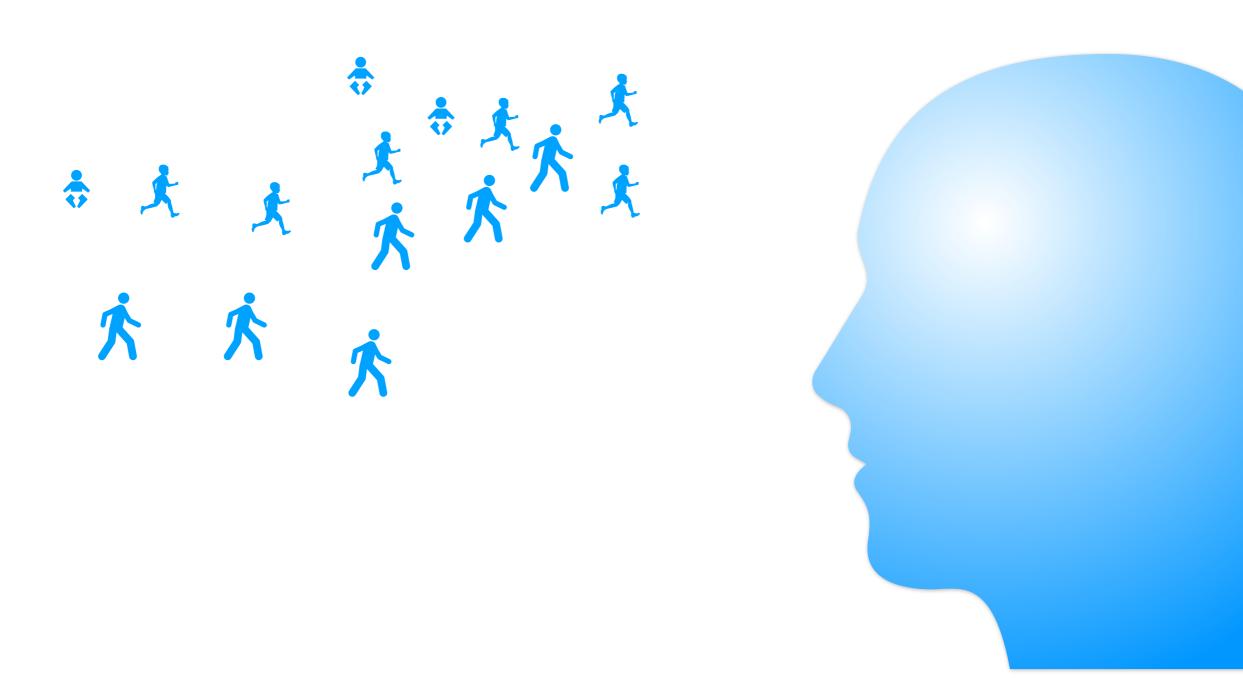
Process for new business

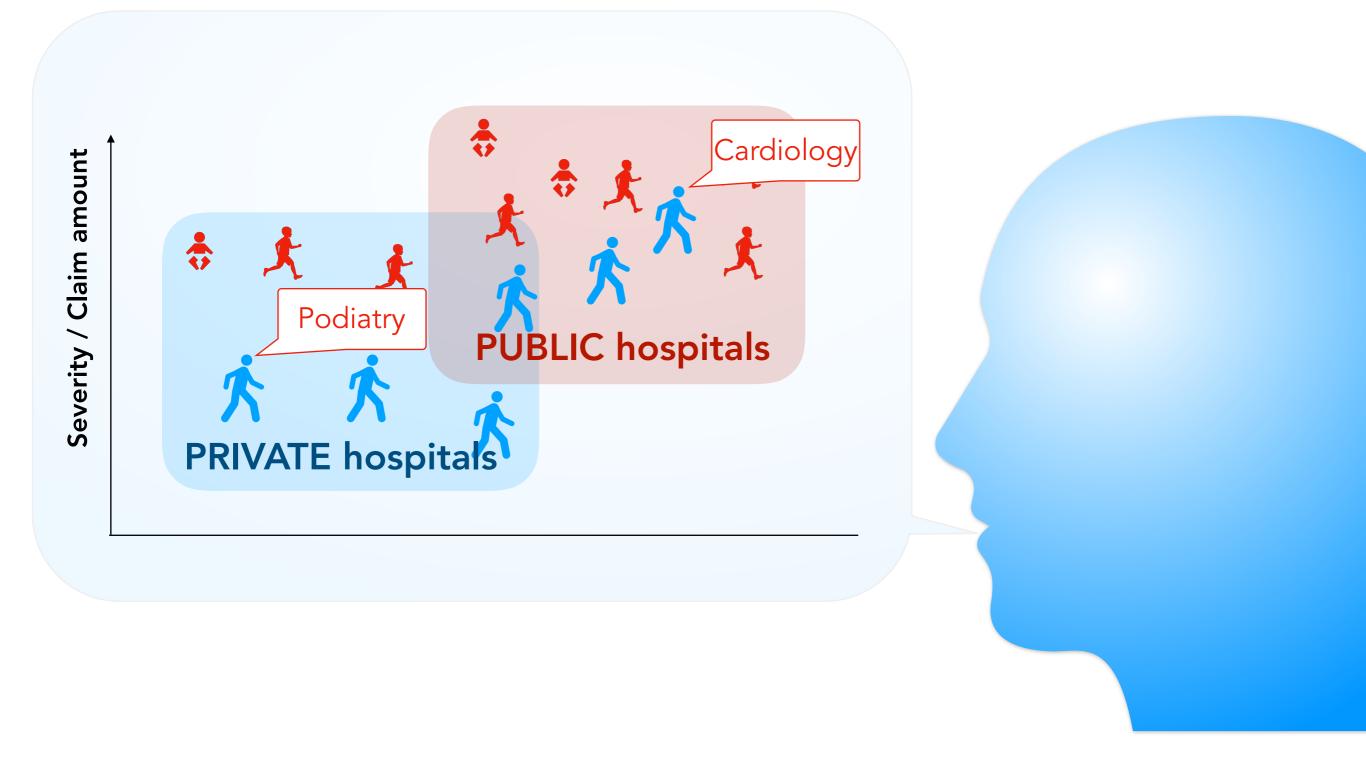






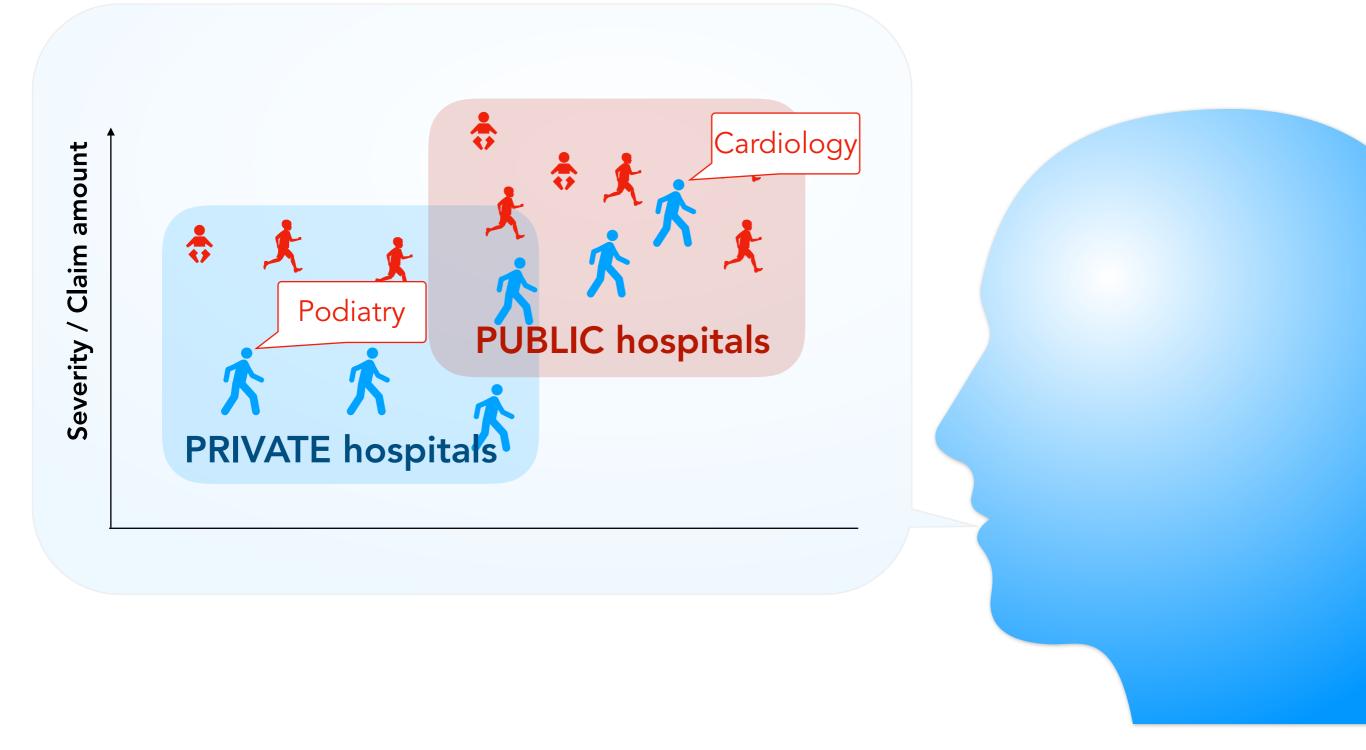
Quicker and Better?



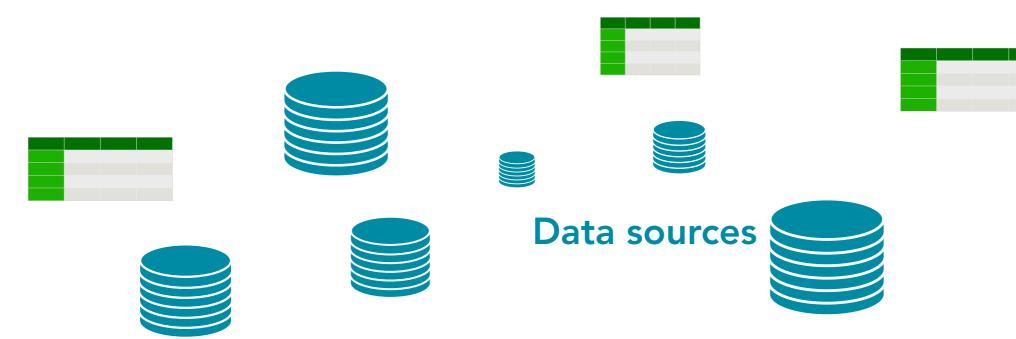


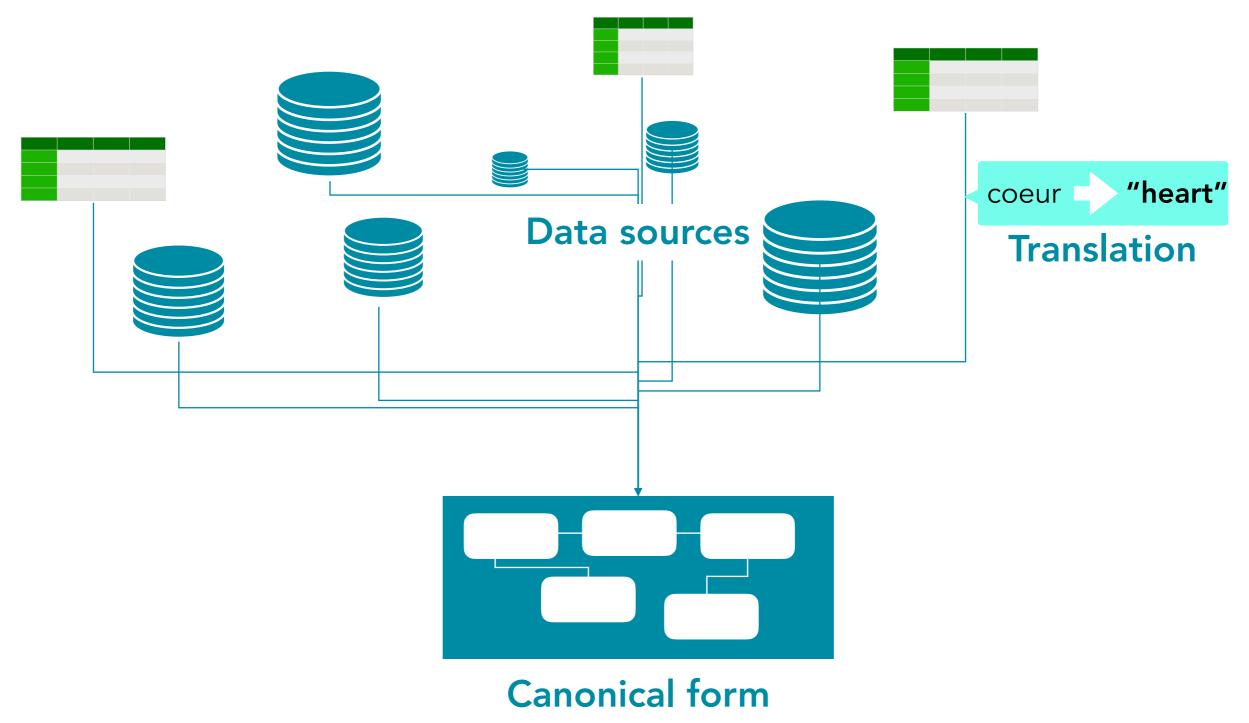


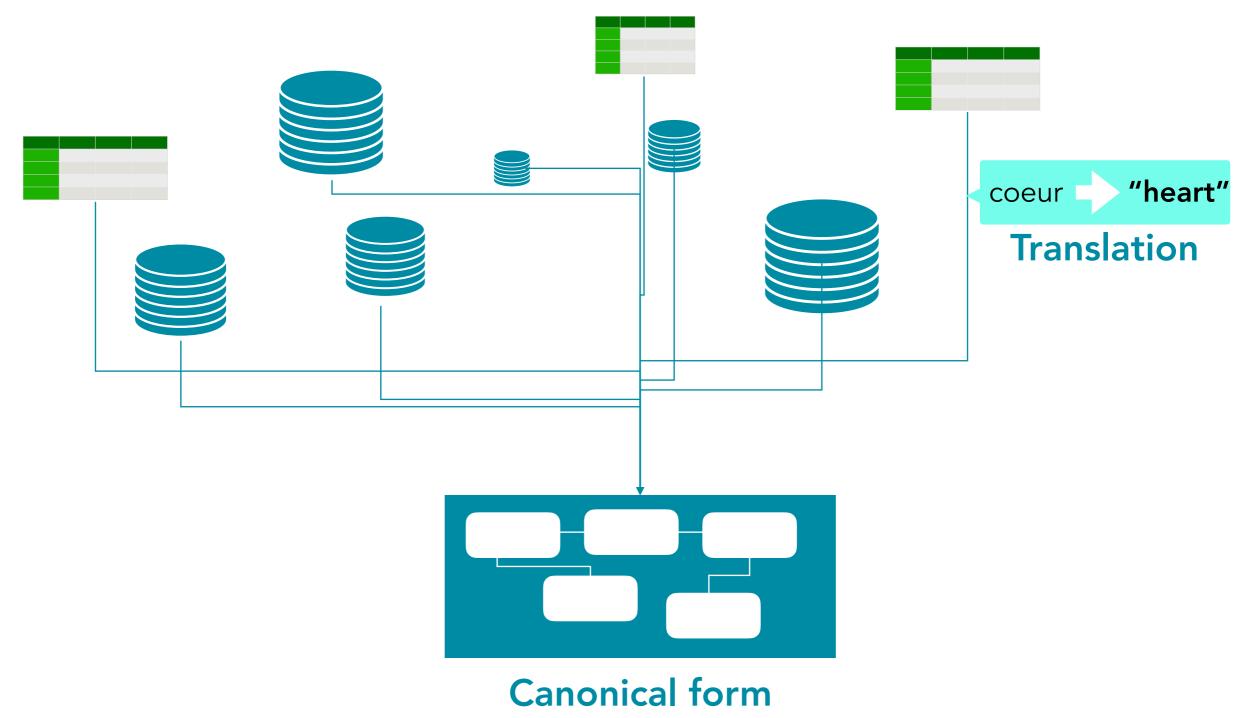


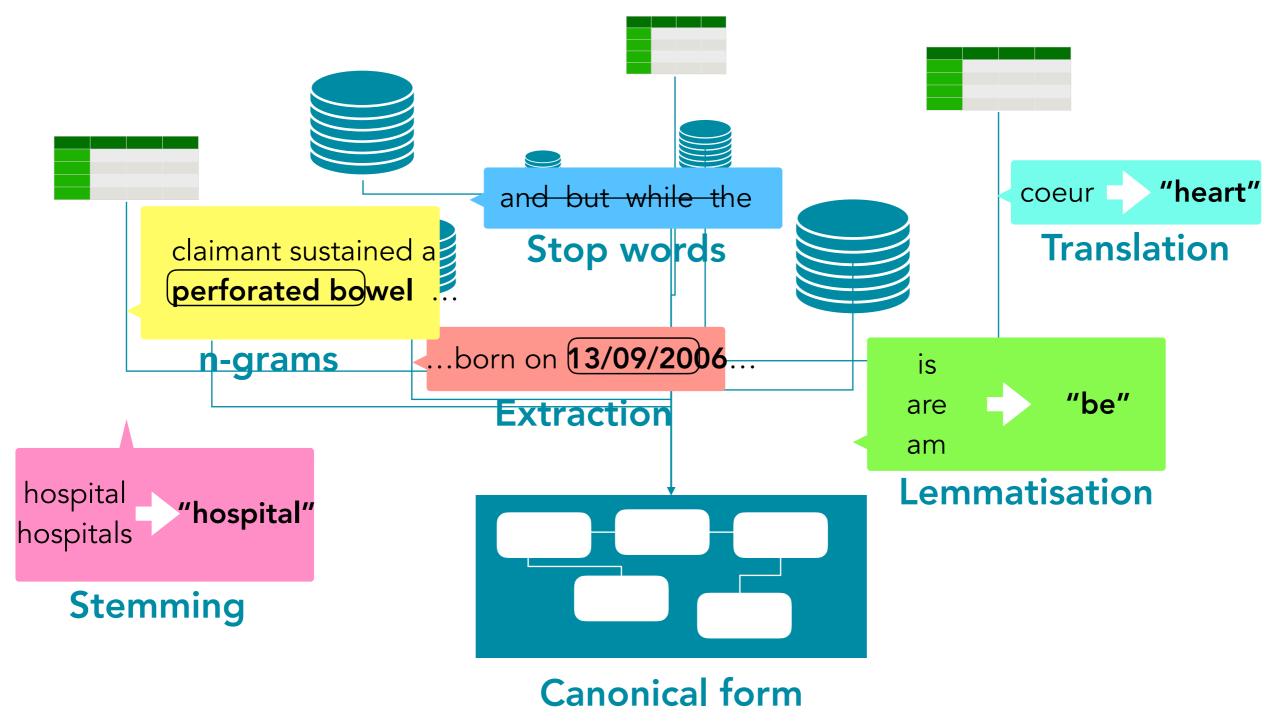








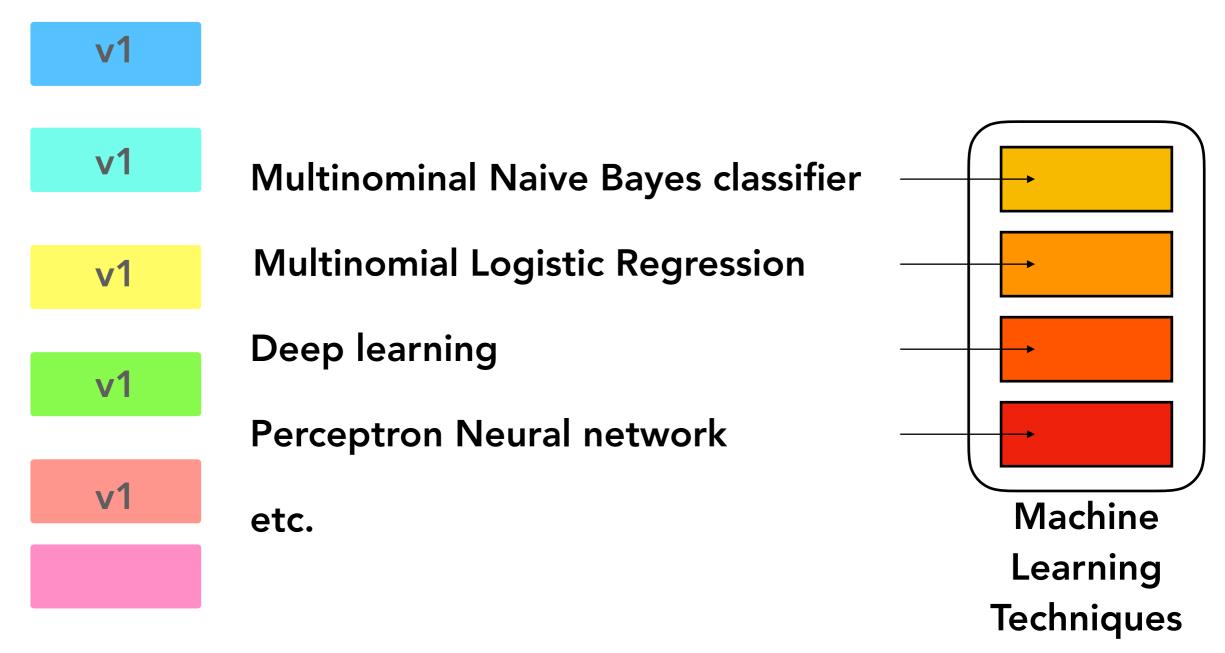




v1	Ma	achine Learning
v1		
v1	Multinominal Naive Bayes classifier	
v1	Multinomial Logistic Regression	
v1	Deep learning	
	Perceptron Neural network	
v1	etc.	Machine Learning Techniques

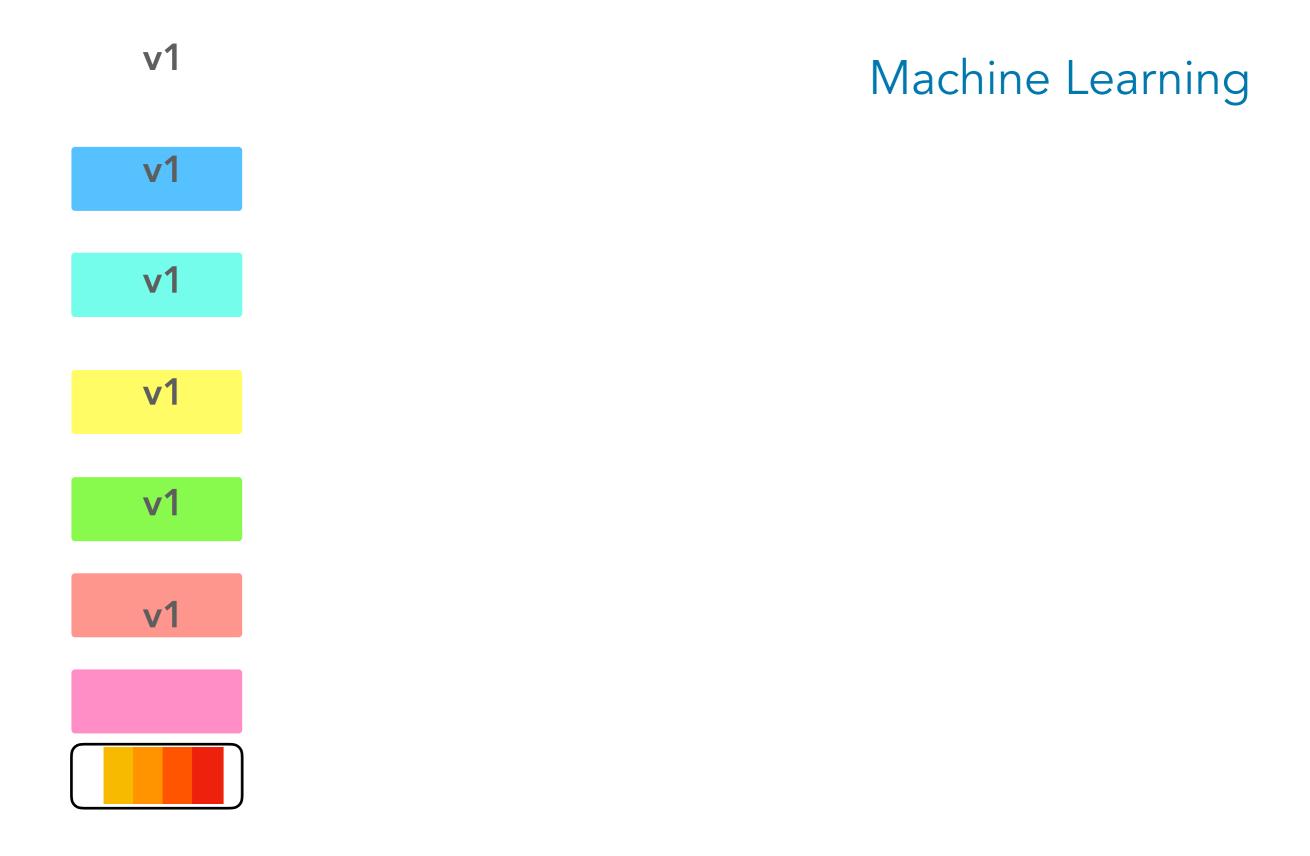
v1 Machine Learning **v1** v1 **Multinominal Naive Bayes classifier Multinomial Logistic Regression** v1 Deep learning v1 **Perceptron Neural network** v1 Machine etc. Learning **Techniques**

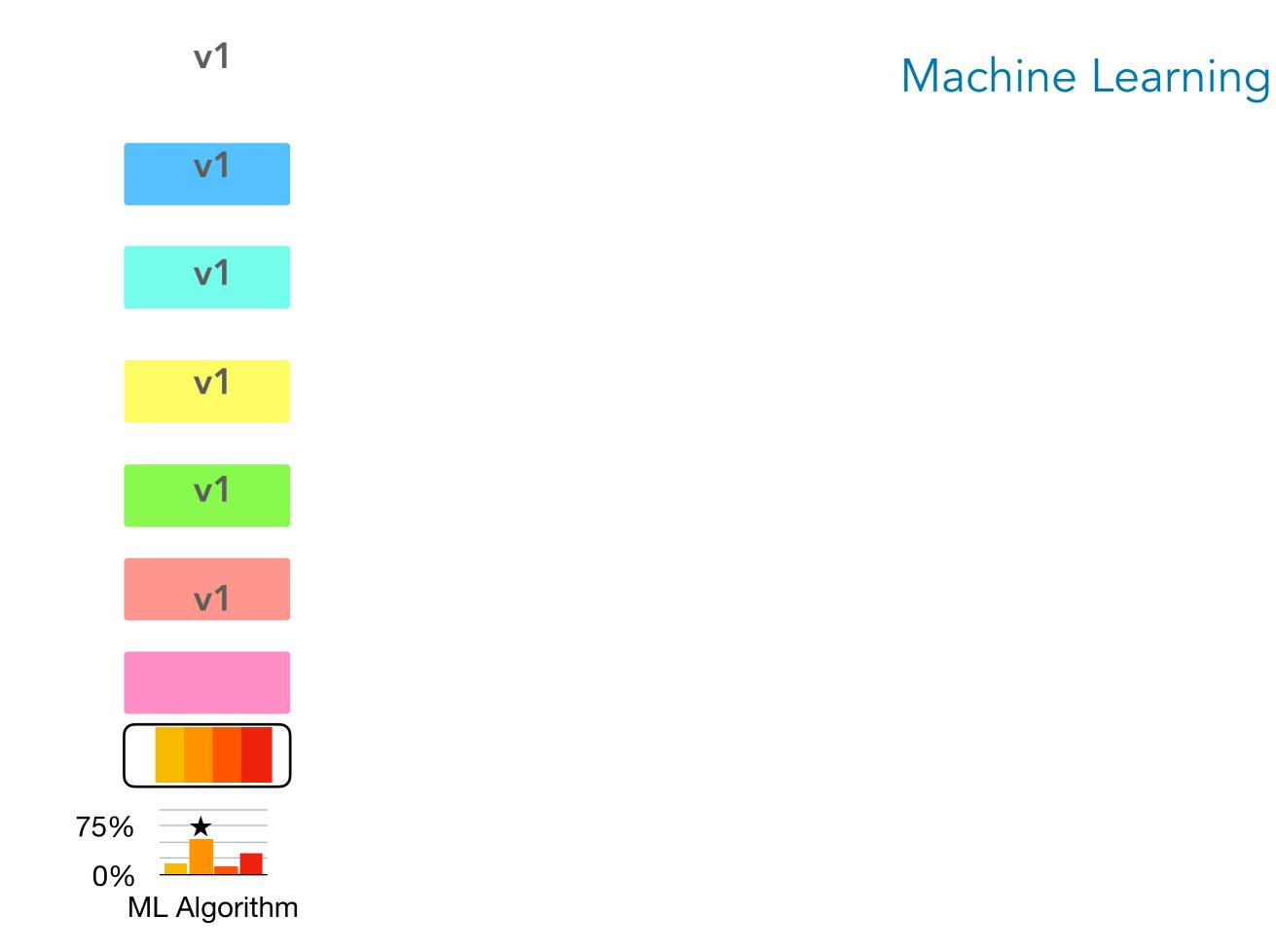
NLP techniques

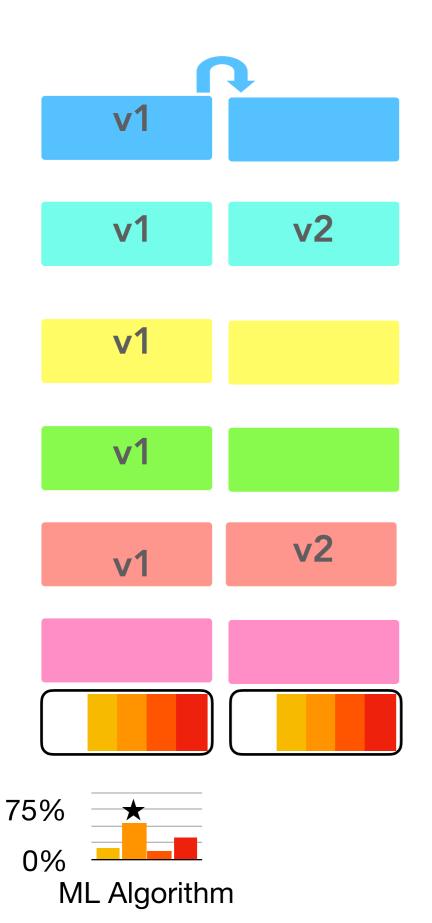


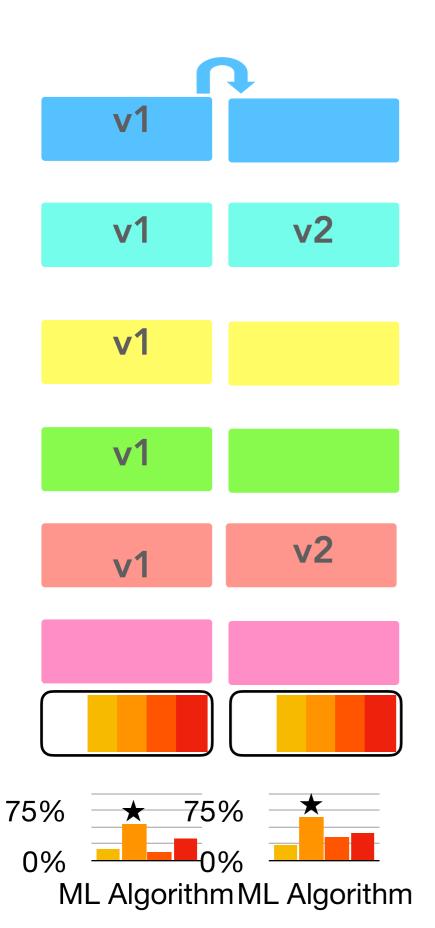
NLP techniques

v1

















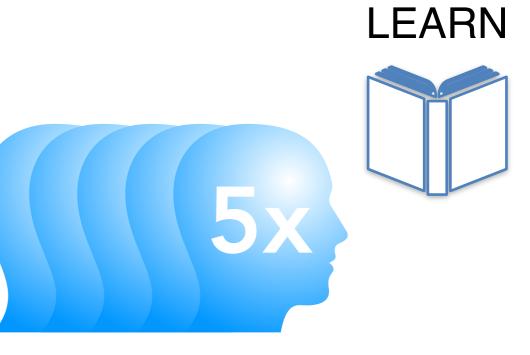




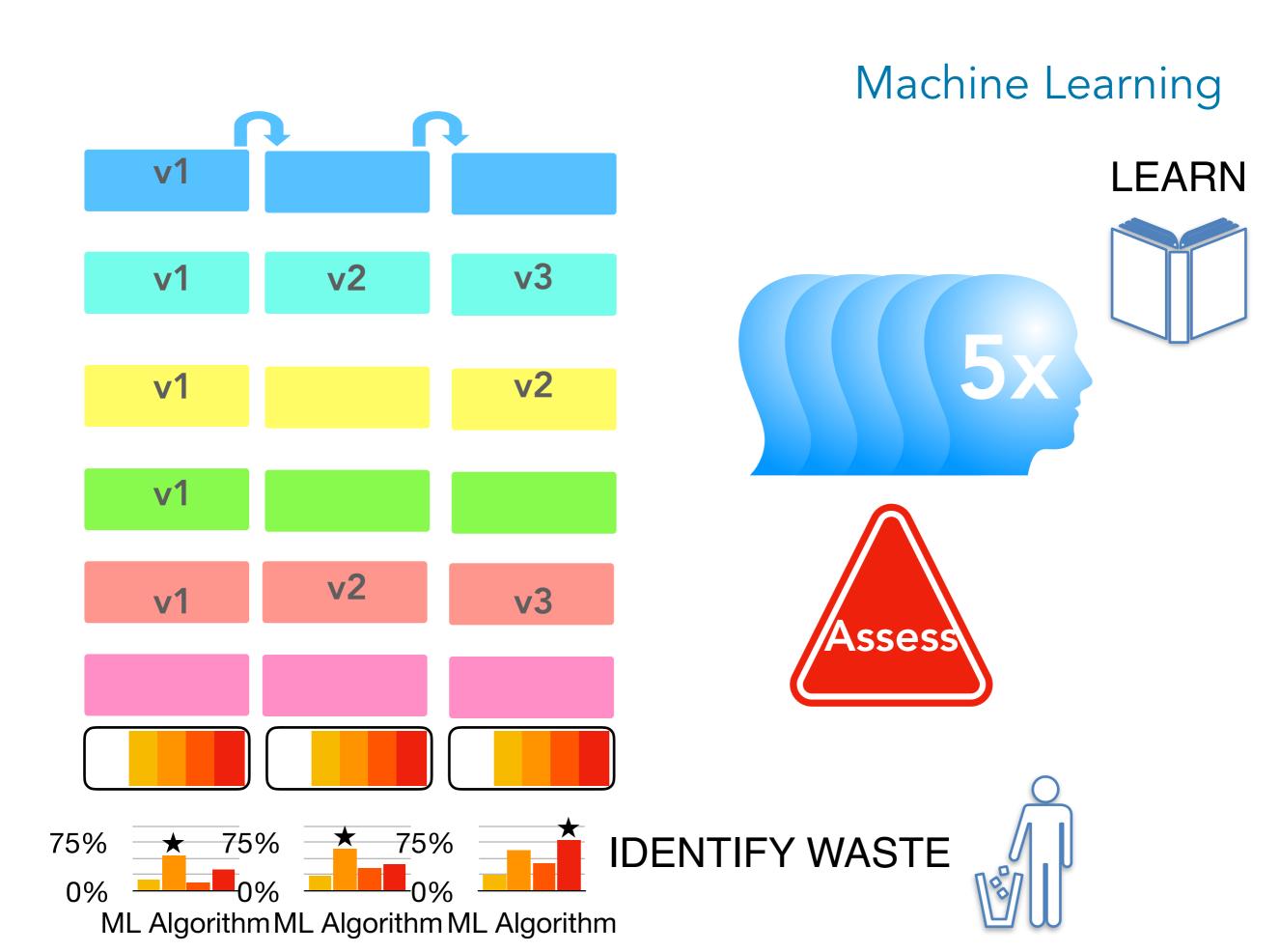














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Results									
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1237		Multinominal Naive Bayes	data-1529499889365.csv	unigrams	37 %	37 %	88 %	56 %	3
1236		Logistic Regression	mca_extract_all_12_07_18.c	unigrams	32 %	0 %	85 %	0 %	3
1235		Decision Tree	mca_extract_all_12_07_18.c	unigrams	36 %	0 %	87 %	0 %	3
1234		Multinominal Naive Bayes	mca_extract_all_12_07_18.c	unigrams	30 %	0 %	74 %	0 %	1
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Results									
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Lessons

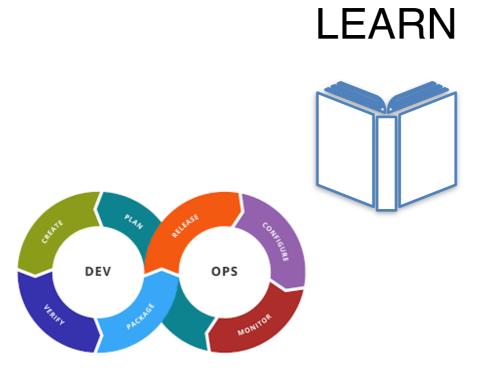


Lessons











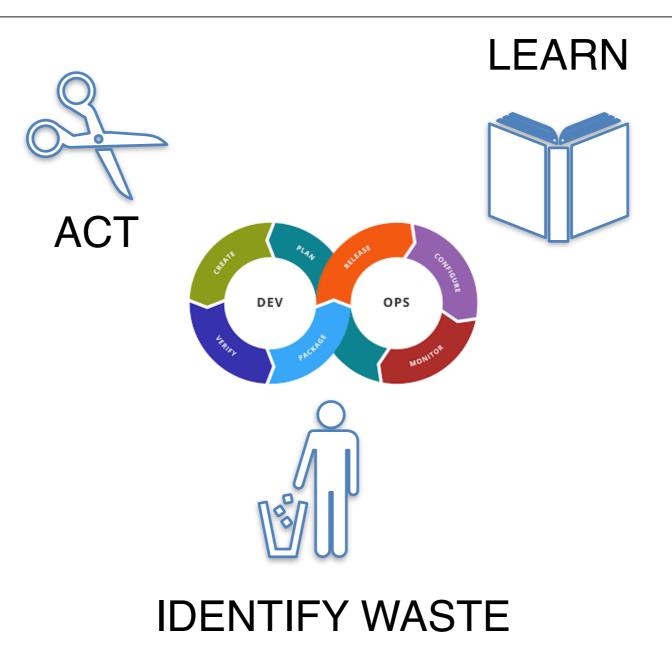




IDENTIFY WASTE









Say hello to us at stand #12



Innovate | Deliver | Transform

Say hello to us at stand #12