

# Al that cares about your broadband connection

Spark+Al Summit Europe - Oct. 2018



Head of Data Science, DMTS Digital Experience - Analytics Nokia Software

**#SAISEnt6** 



### Nokia



2000



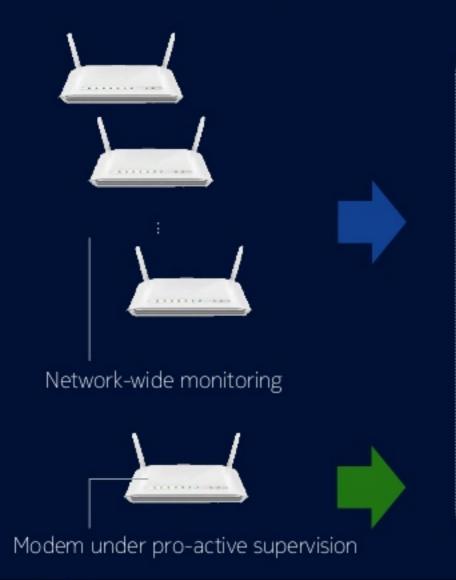
# Powered by Al

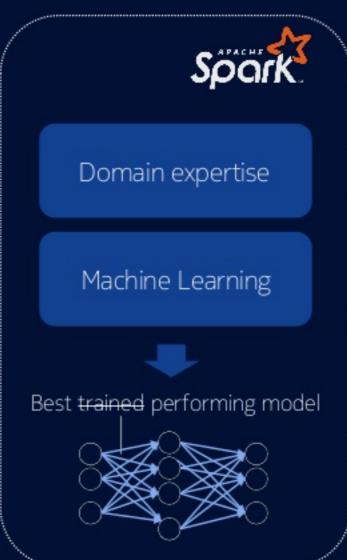
# Care Analytics

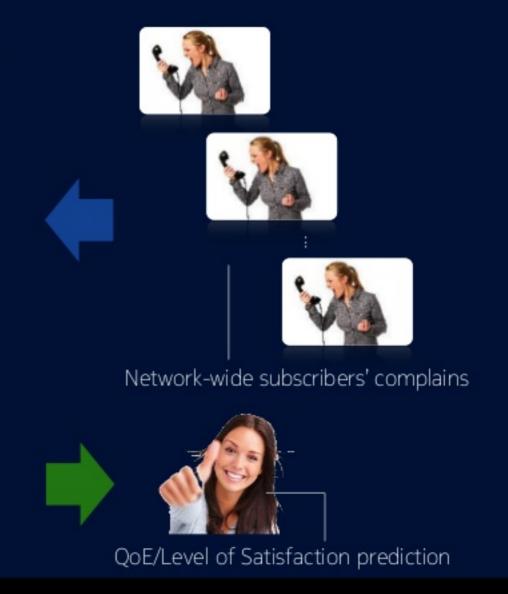


Digital Experience







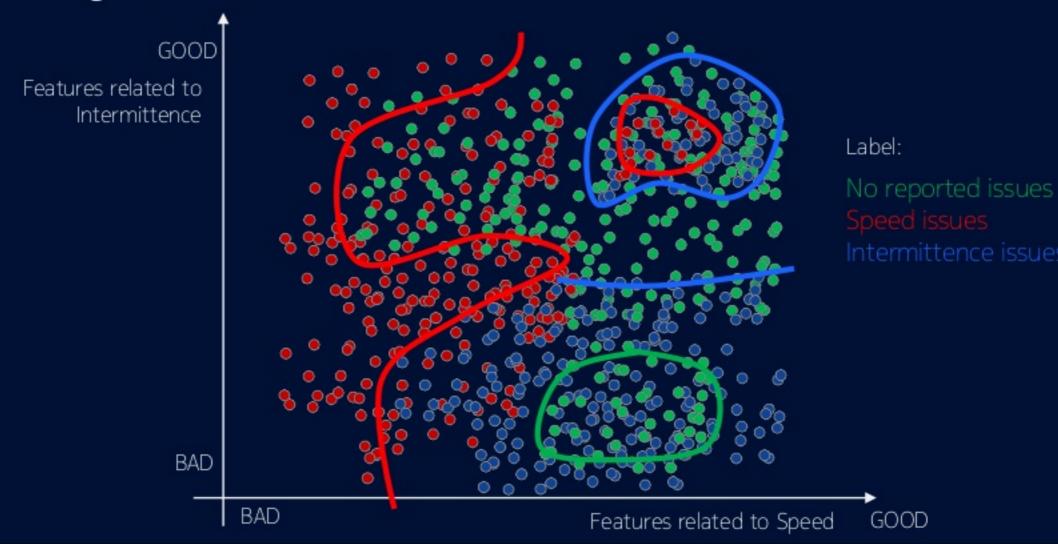


Pattern recognition Because of: Domain expertise Data transformation KPI's computation Lack of information a resampling step, based on pattern recognition, Performance validation Scope/requirements has Ledo added to the process. Interpretation How to measure performances Model selection Time-series FE Modelling Balancing Machine Learning





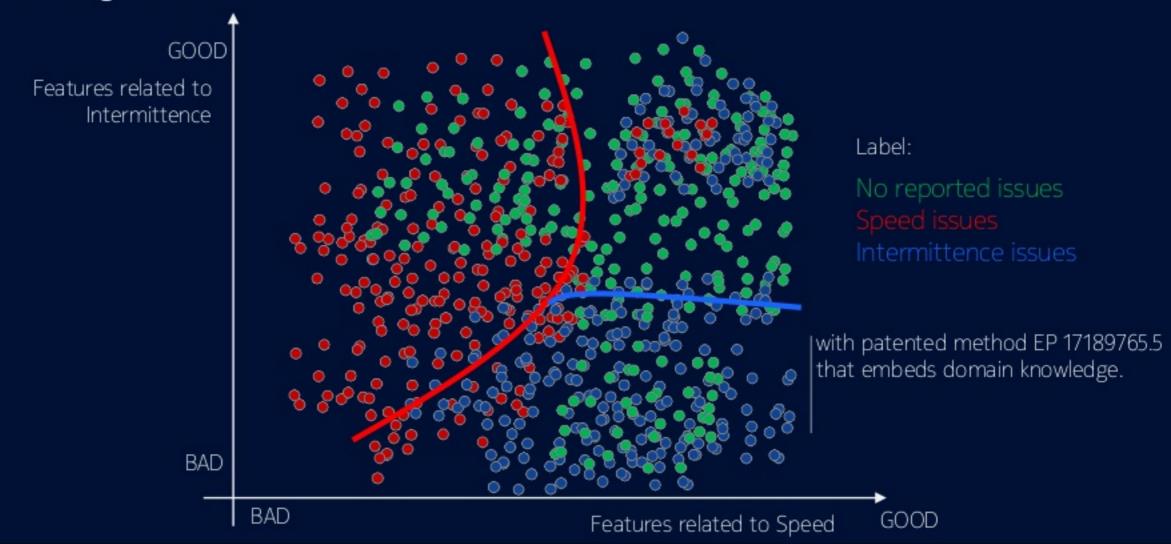
Pattern recognition







Pattern recognition









- ETL
- Windowing/Pre-processing over >100M data rows
- Spark MLlib
- Efficient/distributed learning
- Execution



- Complete Spark MLlib API
- Java world
- Ability to produce JAR files



- Executed as Spark jobs
- Compiled code



Empirical algorithms

Machine Learning

Machine Learning + domain knowledge

Prediction LIFT (gain)

Field performances

10x

女

80x

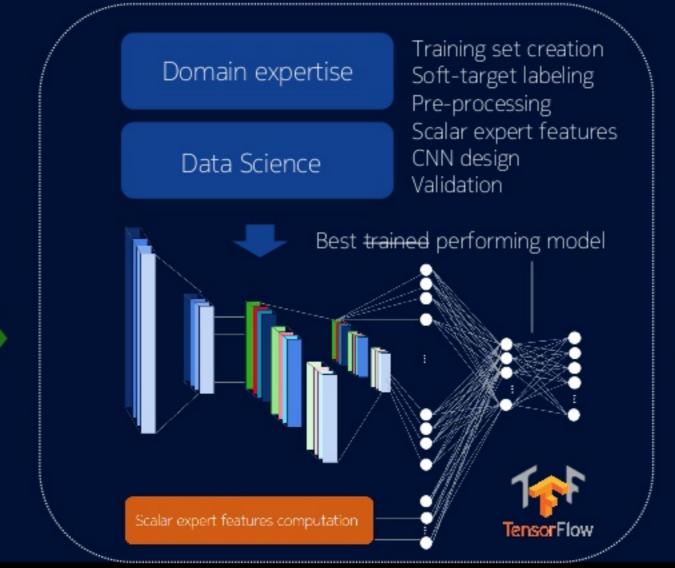
\*

80x

\*\*\*

Predictions much valuable for the business.











Modem under pro-active

supervision



Soft-target labeling

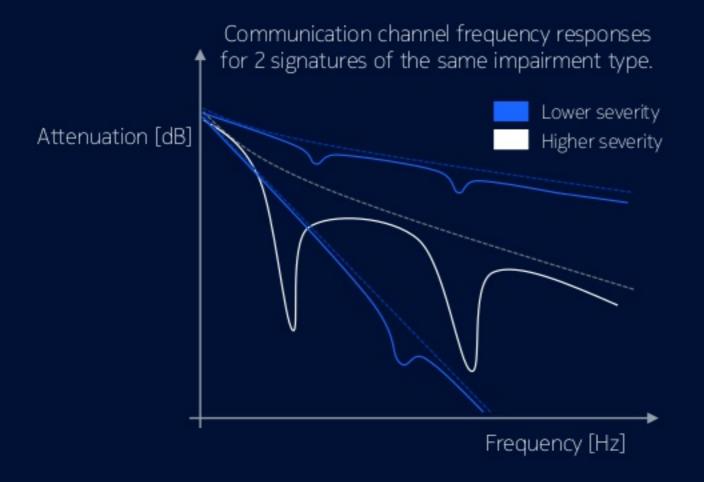
```
0000000000
/11/1/////
2222222
333333333
V A 4 4 4 4 4 4 4 4
555555555
6666666666
フフフクチフワクフフ
888888888
999999999
```

- « Experts » (e.g. humans, authors) labelled formally each digit.
- No ambiguity is assumed during the training set creation (hard-labelling).

MNIST handwritten digits



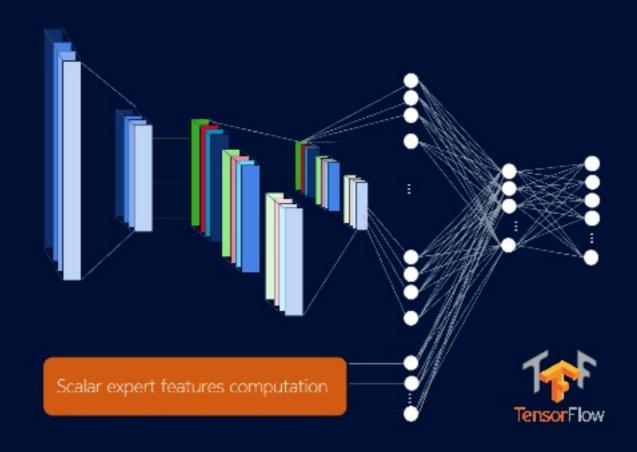
### Soft-target labeling



- In problem detection, there is the notion of « severity ».
- This means within the same class of problem, the returned confidence needs also to reflect such severity.
- Solution is to make use of softlabelling.
- Domain knowledge is required to assist deriving such soft-labels.
- Spark! has been used to facilitate such processing over >20M curves.



Expert scalar features addition



- Having the « perfect trained model » would require to build the « perfect training set ».
- Building a large, various and unbiased training set is hard.
- The convolutional layers might get therefore biased, leading to extra sensitivity.
- Adding empirical quantities to the fully-connected layer have helped in gaining in robustness (conservative approach).









- CNN model design
- Training over >20M samples
- Expert scalar features computation
- Trained model/session storage

- Pre-processing
- TensorFlow Python API

- Soft-target labelling
- Hyper-parameter tuning (« grid search ») distribution
- Distributed execution





	Empirical algorithms	Machine Learning	Deep Learning	Deep Learning + domain knowledge
Top accuracy	<50%*	>85%	>96%	>97%
Foot false positive rate	>20%*	<5%	<1%	<0.1%
Field performances	*	女女	女女	***
		Quality of insig	ghts much valuable	for the business.

<sup>\*</sup> Narrower coverage.





### Last advices...

- Data Science gives always better results when you know what is behind the data.
- Increasing your domain knowledge will save you a lot of time (and will make you a better data scientist ☺).
- ML/DL models that perform well in Notebooks may not give expected results in the field. Knowing how to move forward is the key!
- DL models usually performs better when guided with domain expertise.
- Try to get domain experts and data scientists in the same team.



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