Stories that Data Tells: A Practitioner's Perspective

Shonali Krishnaswamy





Artificial Intelligence

Unsupervised Machine Learning - Novelty and Drift



Deep/Multi-Layered Learning

Award winning proprietary multi-layered ML methodology



Advanced Analytics

Al plus DL operating on multimodal data

- Structured and Unstructured

AIDA Team's Past Track Record



insurance consumers' needs

By Lee Meixian leemx@sph.com.sg @LeeMeixianBT

'Engaging industry' a key priority in boosting S'pore as an R&D bub: NRF

AIA Group to up stake in Indian life insurance JV with

SMRT partners



Hot stocks: Keppel and Sembcorp Marine fall more

MORE FROM THE BUSINESS TIMES

Temasek fund invests undisclosed



possible buyer in 3

COMPUTERWORLD

Standard Chartered partners A*STAR's



S'pore team tops in predicting flight timings

with solution that could help airlines save millions of dollars

Electric decided to find a soluthe launched the GE Flight with a prize of US\$100,000

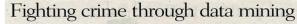




App tells you if place is hot spot or dead town

Software identifies crooked sellers faster

Built by Visa and A*Star, i



credit card company to detect fraud using advanced data analytics technology. OO GIN LEE reports

relevant information/services to mobile users.

SingTel and I2R Joint Laboratory

12R has announced its partnership with SingTel to set up a joint laboratory eyare at

to develop advanced data analytics for innovative, personalised and





thesundaytim



es **asiare**p

THE STRAITS TIMES







GE Report Forbes



Multi-Award Winning Machine Learning Team

AIDA Won the Monetary Authority of Singapore Hackcelerator Inaugural Singapore FinTech Festival 2016

http://www.fintechfestival.sg/hackcelerator/www.aidatech.io



100 Problem Statements, 650 Submissions, 20 Finalists and 3 Winners









2011

1st Place in ALL 4
Categories:

EU OPPORTUNITY Mobile Activity Recognition Challenge 2015

1st Place: IJCAI Repeat Buyer Prediction in E-Commerce — <u>Beat</u>

754 Data Scientists

1st Place: ACM KDD Cup Predictive Analytics – **Beat 821 intl' teams**

2015

1st Place: Springleaf Sponsored Kaggle Marketing Response Competition — **Beat 2,225 international teams**

IES Prestigious Engineering Award

2016

IES Prestigious Engineering Award

ASEAN Outstanding Engineering Achievement



Key Take Away #1: Its ...the FEATURES...!

E-Commerce Repeat Buyer Prediction

International Joint Conference in Artificial Intelligence 2015 1st Place out of 754 international teams

- 260,000+ "loyal" customer + merchant pairs provided as training data
- Predict the repeat buying probability of other 261,000 user and merchant pairs

user	item	category	merchant	brand	time	event
048300	436606	0204	0731	5417	1110	add2cart
328862	844400	1271	2882	2661	0829	click
328862	81766	0614	4605	7622	0709	buy
328862	524981	0664	2382	1272	0602	click
328862	440930	1271	2882	2661	0829	click
244974	218624	0451	1503		1109	add2cart
328862	575153	1271	2882	2661	0829	favourite
		•••				

Question:

User "048300" will be a loyal customer of merchant "0731" in the future?





65.00 %

AIDA Scientist
Part of Winning Team

70.50 %

Direct Email Marketing Campaign

Kaggle - Springleaf Marketing Response Competition 2015 1ST Place out of 2,225 international teams

- Customer data: Anonymized, messy (strings and numbers) and high dimensional
- Column names range from VAR001 to VAR1934
- Column value can be a number or date or hash string No meaningful explanations

Question:

Will user "X" respond to a direct email campaign?

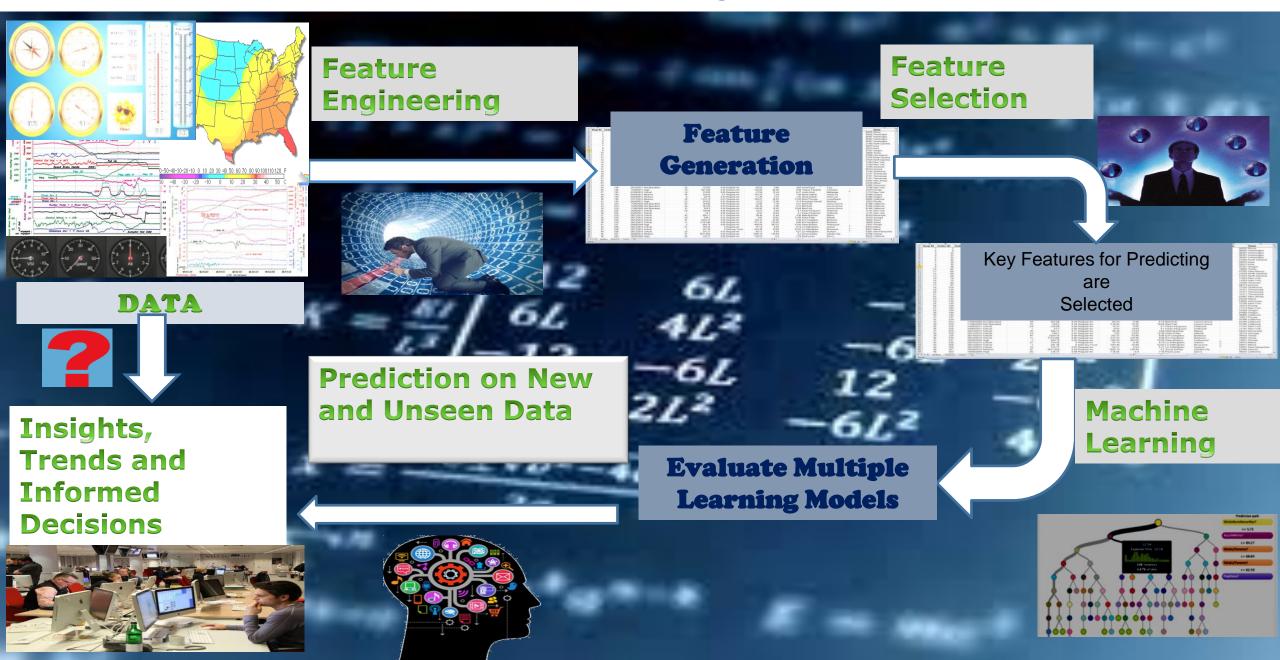
Solution:

AIDA

Team Member Winning Solution –

80.39%

Machine Learning Process





Key Take Away #2: Algorithm Design and Choice – Horses for Courses!

Unsupervised Concept Drift Detection: Early Detection of Change







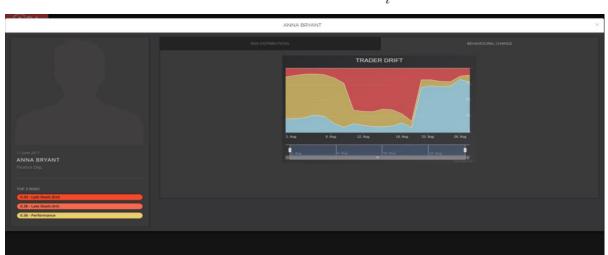
Changing Lifestyle and Life Stages



Monitoring for Risk Profiles

ConTrack: An unsupervised concept drift detection method that can:

- (1) track K concepts $B_{k}^{(t)}$ that are shared amongst the N actors
- (2) track each of the N actors' participation $\theta^{(t)}$ in the K concepts



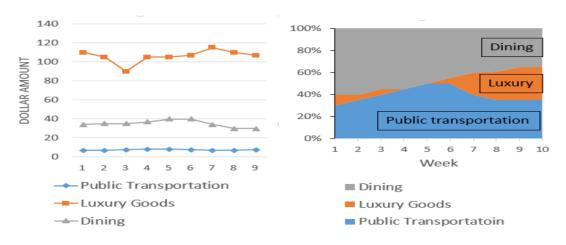


Figure 1: Visualization of changes in actor participations and concepts in banking data. **Left:** Tracking the changes in dollar amount dimension of public transportation, dining and luxury goods concepts over time. **Right:** Tracking the changes in actor's participation for public transportation, dining and luxury good concepts over time.

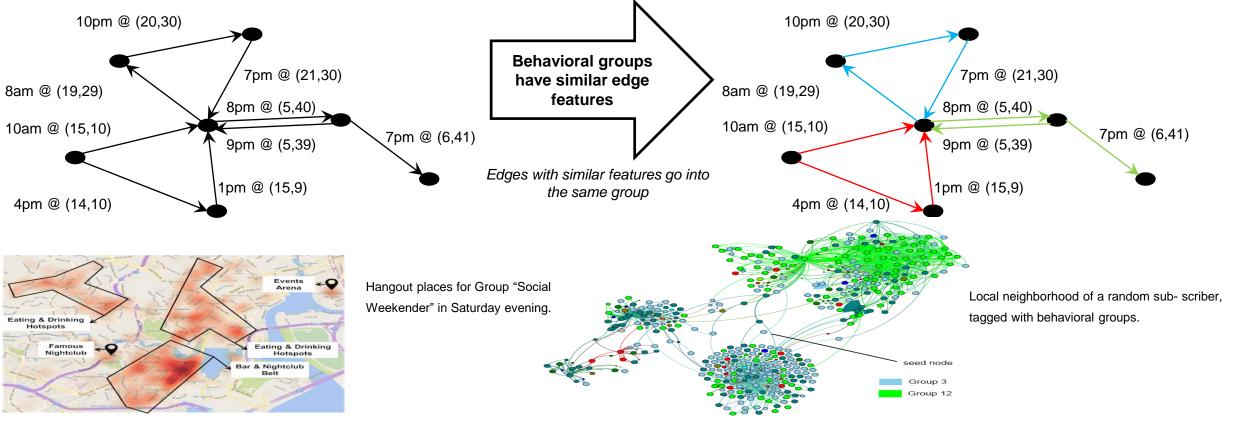
Identifying Behavioural Groups from Telco / CDR Data

Problem: Derive behavioral groups from CDR Data.

Solution: Behavioural Groups have similar Edge Features.

Distributed Graph Edge Clustering (DGEC) is an optimization model that discovers:

- 1) K behavioral groups within service/network graphs (which are directed, multi-edge, and have features on each edge)
- (2) which of the K behavioral groups each edge and node is affiliated with (where nodes can belong to multiple groups)





Key Take Away #3: Modelling a Problem in Machine Learning Terms – *Half the Battle!*

AI-CLAIMS: AI Driven Analytics for Claims Management

Improving
Processes and
Customer
Experience

Machine Learning for Information
Extraction & Predictive Claims
Processing

Augmented Intelligence for Claims Management



Managing Evolving Risks

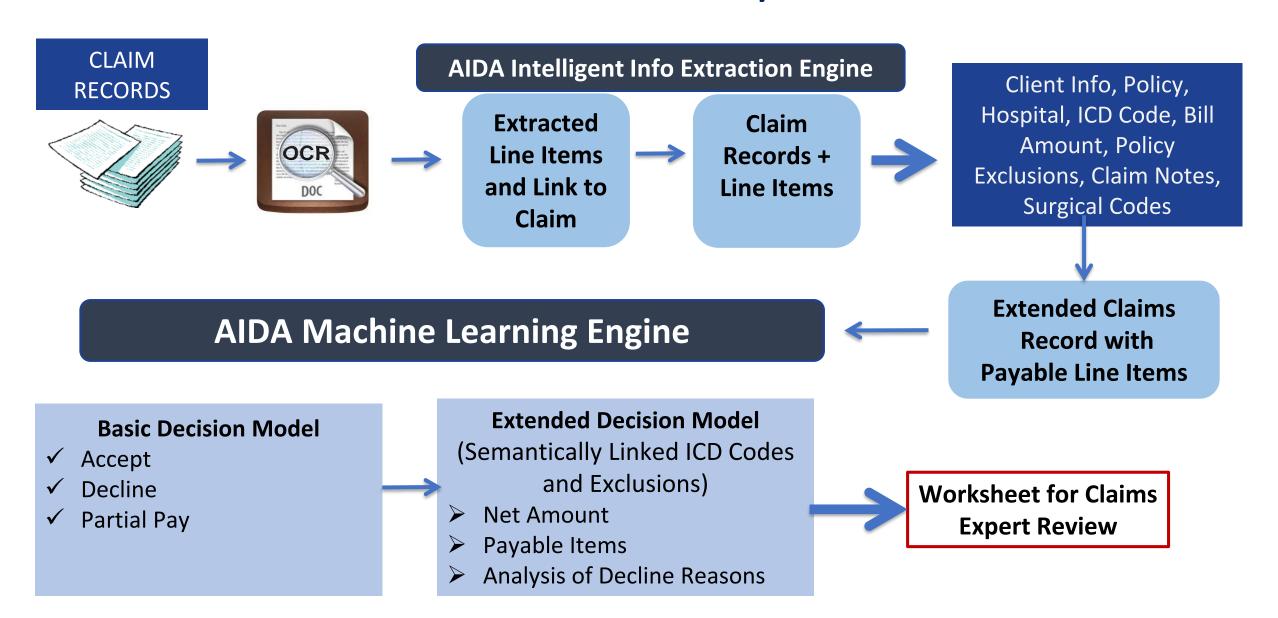


CLAIMS

Increasing
Revenue and
Reducing Cost

Predicting Modelling for Propensity to Claim

AIDA AI-CLAIMS System



Deep Learning to Learn Contextual Connections

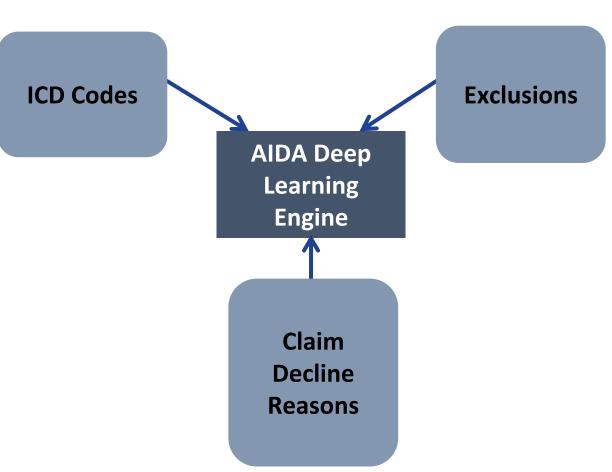
Contextual and Intelligent Linking of Text Data

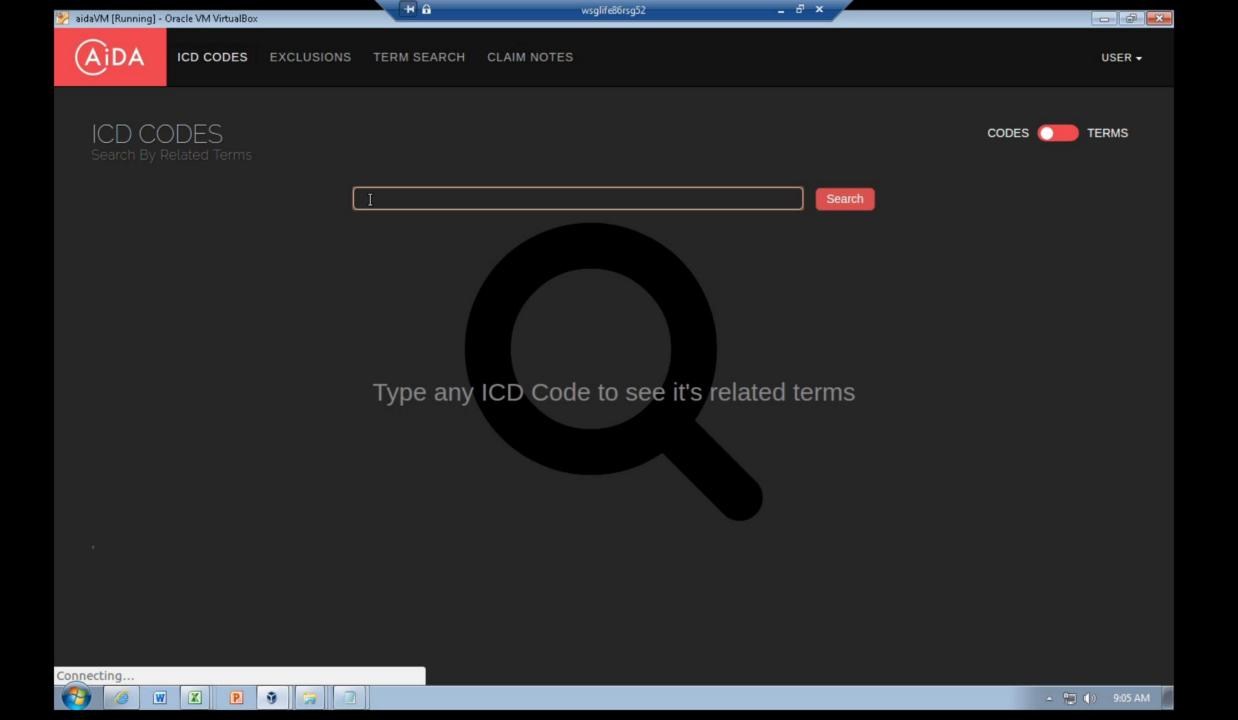
Key Challenge

- ☐ ICD Codes and Exclusions are Not Semantically Linked
- ☐ ICD Codes are in Medical Terms (e.g. Obstetrics)
- ☐ Exclusions are in Layman's Terms (e.g. Maternity)

AIDA AI-CLAIMS Text Mining Engine Automatically Learns Contextual Connections from Text Data

- Connect Terms to ICD Codes
- Connect Terms to Exclusions
- Connect ICD Codes to Related ICD Codes
- Connect Exclusion Codes to ICD Codes







Key Take Away #4: Imbalance is a Very Real Challenge!

Profitability Modelling

Categories 2015-2016	Count	%
Total No. of Customers	XXXX	100
Total Number of Profitable Customers (Premium – Total Claims/ Premium) = 0	XXXX	91.x
Total No. of Medium Profitable Customers (0 < (Premium – Total Claims/ Premium) < 1	XXXX	3.x
Total Number of Non Profitable Customers (Premium – Total Claims/ Premium) < 0	XXXX	5.x

Revenue (\$)

Total Revenue : R
Total Claims Value: C
Total Profit : R-C

Comparison of Models

Approach	Model Accuracy	No. of Non- Profitable Cases	Number Correctly Identified	Total Cost (Value of Claims in \$)
Business As Usual	N/A	XXXX	None	X %
Predictive Model #1 (Naïve)	91%	XXXX	1	X %
Predictive Model #2 (With Imbalance Factored)	82%	XXXX	625	Approx. Claims Cost Reduction By 30 %



Key Take Away #5: Not All Metrics Contribute to Adoption and Usability!

Machine Learning Metrics

- **✓** General Sense of Model Performance
- ✓ Useful for Model to Model Comparison

Predict X (X=Good Customer)	Actual X	
1	1	→ True Positive (TP)
1	1	
1	1	How many did the model
1	1	NOT CATCH ?
0	1	→ False Negative (FN)
1	1	
0	1	How many did the model GET WRONG?
1	0	→ False Positive (FP)
0	0	
0	0	→ True Negative (TN)

ACCURACY: % of Instances Classified Correctly

Precision = True Positive / (True Positive + False Positive)

Recall = True Positive / (True Positive + False Negative)

F-Score: A combined measure that considers both *Precision* and *Recall*

Area Under the Curve (AUC): Different true positive/false positive rates using a threshold. As you decrease the threshold, you get more true positives, but also more false positives.

Lift (For Imbalanced Data):

What is the impact of the Model Vs Random?

E.G. 100 Retained Customers among the 10,000.

Randomly select 10% of population (1000), you can potentially identify 10 customers. If you select Top 10% of the Model, if you can identify 60 customers, then Lift is 60 / 10 = 6.

How to Adopt Machine Learning: Business Metrics

Date	Customer ID	Machine Confidence	Prediction for Good Customer
1/1/2017	MUM001	0.85	Yes
1/1/2017	CHE008	1.0	Yes
1/1/2017	CHA009	0.2	No
4		0.4	No
5		0.5	No
6		0.6	No
7		0.7	Yes
8		0.8	Yes
9		0.85	Yes
10		0.9	Yes
12		0.9	Yes
13		0.82	Yes
14		0.1	No

1. What is the Acceptance Threshold?

At What Threshold is the Machine Confidence Guaranteed to Get Most of it Right? (e.g. 80% confidence, has 99 % accuracy, *n* false positives and *m* false negatives)

2. What is the Support/ Coverage (number of instances) above this Threshold?

(e.g. 80% confidence has 50 % Support)

A Good Acceptance Threshold must have *high accuracy* above the threshold and *high support*.

Metrics for Model Decline and Data Changes?





What's Next?

History / Data



User/Activity/ Task
Observations

What's Next?



Learning from Data + Knowledge / Context + Feedback



Learn 2 Learn

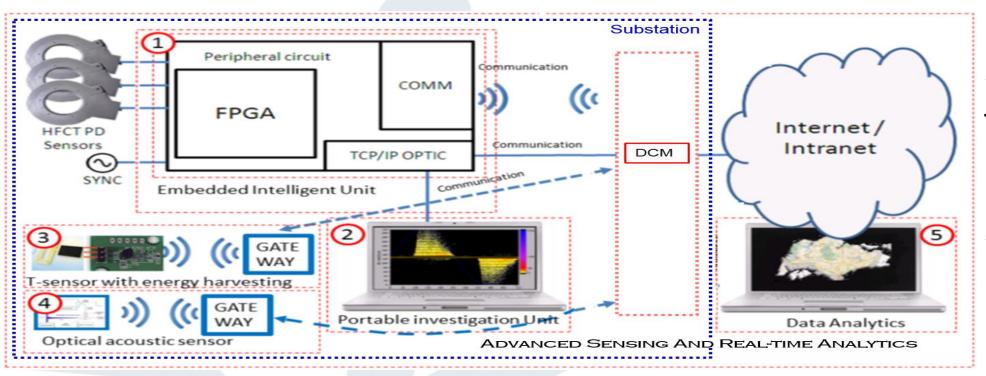


Feedback from User



Domain Knowledge / Semantics / Context

Distributed and Onboard Analytics: Many Open Challenges



Wattalyzer:

An Integrated Solution for Smart Grid Condition Monitoring through Advanced Sensing and Real-Time Analytics

- Sensing
- HFCT sensor : HFCT PD Sensing
- Temperature sensor: Temperature Sensing with Energy Harvest
- Fiber acoustic sensor: Fiber Optic Acoustic Sensing
- Analytics On-board Analytics
 - **Backend Data Analytics**
- **Communication DCM**: Data Communication Management

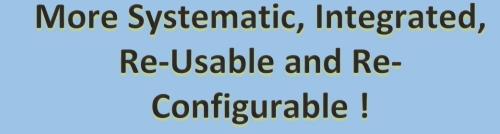
- Reliable and automated
 PD detection
- Integration of sensing and advanced real-time analytics
- Data driven trend analysis and visualization
- Intelligent and timely alerts

Multi-Modal Analytics



0.103	0.176	0.387	0.300	0.379
0,333	0.384	0.564	0.587	0.857
0.421	0.309	0.654	0.729	0.228
0.266	0.750	1.056	0.936	0.911
0.225	0.326	0.643	0.337	0.721
0.187	0.586	0.529	0.340	0.829
0.153	0.485	0.560	0.428	0.628

Structured Data









Unstructured Data - Images



Domain Knowledge and Semantics



Unstructured Data - Text



Data, Data Everywhere!



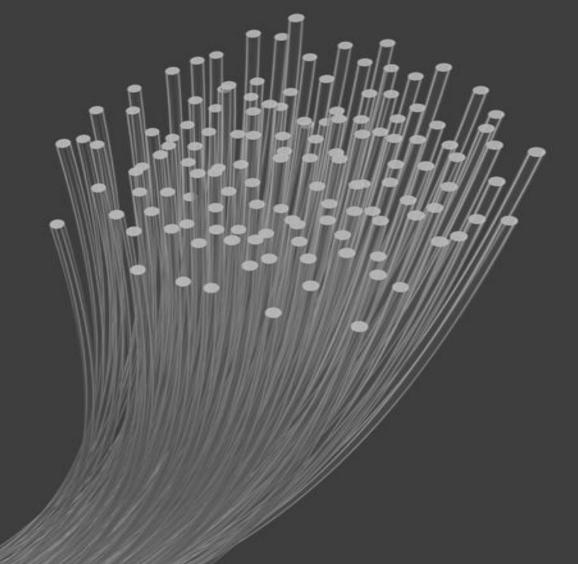
Where is the wisdom we have lost in knowledge?



Where is the knowledge we have lost in information?

The Rock By <u>T. S. Eliot</u> (1888-1965)

Thank YOU!



For more information, please contact:
Shonali Krishnaswamy
shonali@aidatech.io