



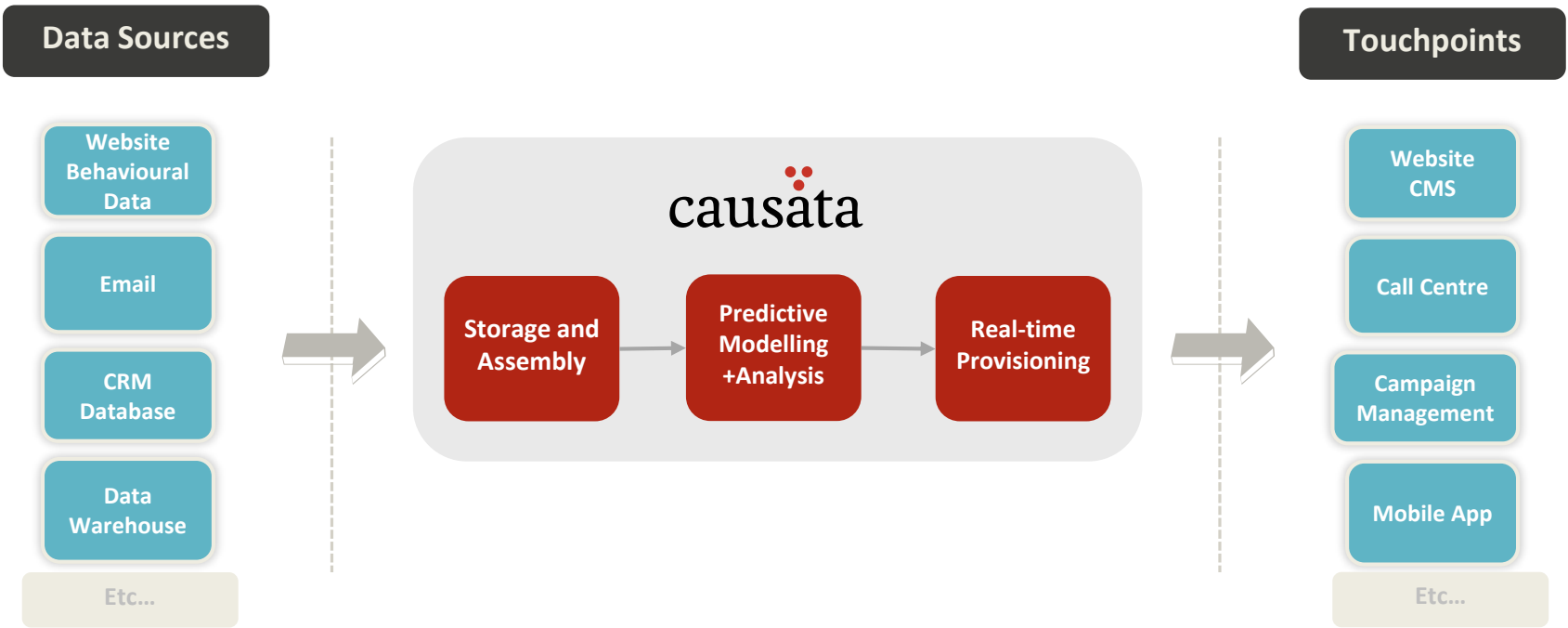
Real-time Decisions on Big Data

Leonard Newnham

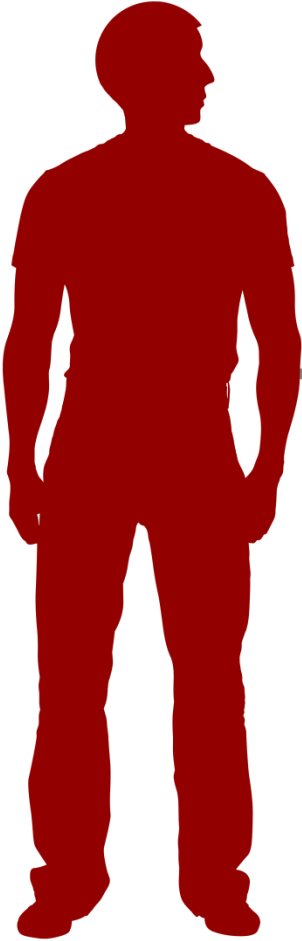
Overview

- Causata data platform
- Automated Decisioning objectives
- Challenges

What We Do and Where We Fit



Customer Interactions



Variable Computation

Total spend
in past month



Select
purchase events over
past month
and extract
price



Apply **sum calculator**



$$13.99 + 259.99 = 273.98$$

Large Number of Variables

- Everything known about the visitor across multiple channels
 - Web data – page view history
 - Call centre data
 - Online accounts
 - Product holdings
 - geo-demographic data
-
-
-
-
-

Large Number of Variables

- Everything known about the visitor across multiple channels
 - Web data – page view history
 - Call centre data
 - Online accounts
 - Product holdings
 - geo-demographic data
- Meta-data on the available actions
 - price point, etc
-
-
-

Large Number of Variables

- Everything known about the visitor across multiple channels
 - Web data – page view history
 - Call centre data
 - Online accounts
 - Product holdings
 - geo-demographic data
- Meta-data on the available actions
 - price point, etc
- Environmental variables
 - Browser language, timezone, etc.

Large Number of Variables

- Everything known about the visitor across multiple channels
 - Web data – page view history
 - Call centre data
 - Online accounts
 - Product holdings
 - geo-demographic data
- Meta-data on the available actions
 - price point, etc
- Environmental variables
 - Browser language, timezone, etc.
- Typically 500+

Requirements

- Gathering data
 - Structure data by individual customer. Assemble all interactions, from many channels, into a complete customer record
 -
 -
 -
 -
 -
 -

Requirements

- Gathering data
 - Structure data by individual customer. Assemble all interactions, from many channels, into a complete customer record
- Making Decisions
 - Retrieve customer record and determine best action with low latency (< 100 ms)
-
-
-
-

Requirements

- Gathering data
 - Structure data by individual customer. Assemble all interactions, from many channels, into a complete customer record
- Making Decisions
 - Retrieve customer record and determine best action with low latency (< 100 ms)
- Displaying Results
 - Visualisation and explanation
 -
 -

Requirements

- Gathering data
 - Structure data by individual customer. Assemble all interactions, from many channels, into a complete customer record
- Making Decisions
 - Retrieve customer record and determine best action with low latency (< 100 ms)
- Displaying Results
 - Visualisation and explanation
- Scale to hundreds of millions of customers

Requirements

- Gathering data
 - Structure data by individual customer. Assemble all interactions, from many channels, into a complete customer record
- Making Decisions
 - Retrieve customer record and determine best action with low latency (< 100 ms)
- Displaying Results
 - Visualisation and explanation
- Scale to hundreds of millions of customers

- Optimise on goals that matter to customer

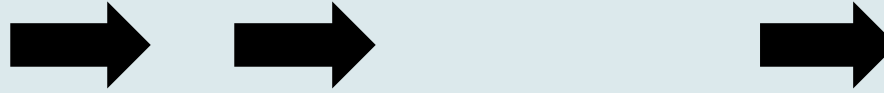
Optimise on Goals that Matter



Optimise on Goals that Matter



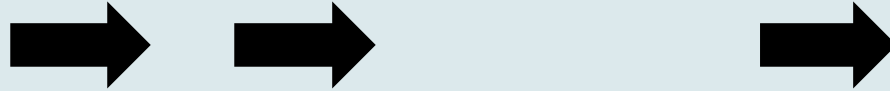
Current state of the art is to locally optimize each interaction, in terms of immediate next step



Optimise on Goals that Matter



Current state of the art is to locally optimize each interaction, in terms of immediate next step



With all the data, can optimize over true **long term business goals**



Why Next Best Action May Not Always be Best

- To maximise long term gain there may be a short term cost:
 -
 -
 -
 -
 -
 -
 -

Why Next Best Action May Not Always be Best

- To maximise long term gain there may be a short term cost:
 - special offers and discounts

-

-

-

-

-

-

Why Next Best Action May Not Always be Best

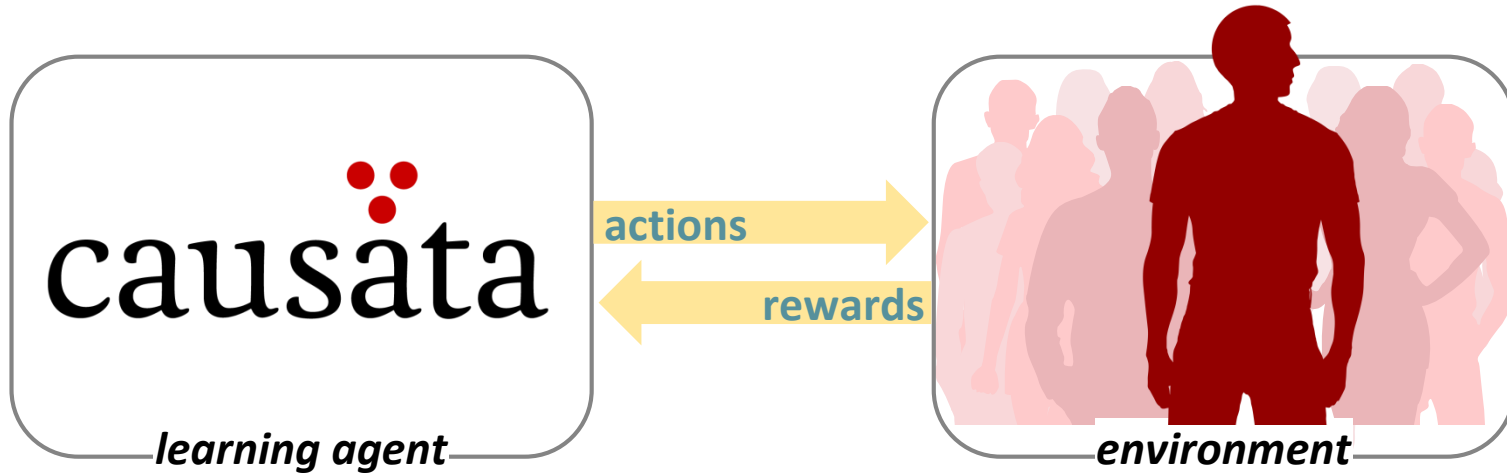
- To maximise long term gain there may be a short term cost:
 - special offers and discounts
- Or a deferred selling opportunity:
 -
 -
 -
 -

Why Next Best Action May Not Always be Best

- To maximise long term gain there may be a short term cost:
 - special offers and discounts
- Or a deferred selling opportunity:
 - restricted number of offers made after sale, eg
 - upgrades options after airline ticket purchase
 - extended warranty
 - Insurance
 - determine best time to send email

Reinforcement Learning

- Choose the actions which will yield the greatest long-term reward
- Reward can be any function we wish to optimize
- Rewards may be deferred to some time in the future



Challenges

- Big Data is not so big sometimes
- Concurrent customer interactions
- Speed of learning
- Visualisation
- Scalability

Big Data is not so Big Sometimes

- Learn objective functions that matter to client (part 2)
 -
 -

Big Data is not so Big Sometimes

- Learn objective functions that matter to client (part 2)
 - Revenue rather than click-through
 -

Big Data is not so Big Sometimes

- Learn objective functions that matter to client (part 2)
 - Revenue rather than click-through
 - Optimise multiple objectives

Big Data is not so Big Sometimes

- Changing Action Set Over Time

- -
 -
 -

-

Big Data is not so Big Sometimes

- Changing Action Set Over Time
 - Individual actions may have a short lifetime
 - Marketing campaigns are frequently limited in time
 - May change due to seasonal variation – - eg summer sales
 - May change due to external factors – eg change of interest rate
 -

Big Data is not so Big Sometimes

- Changing Action Set Over Time
 - Individual actions may have a short lifetime
 - Marketing campaigns are frequently limited in time
 - May change due to seasonal variation – - eg summer sales
 - May change due to external factors – eg change of interest rate
- -> We would like to not learn from scratch with every action change

Big Data is not so Big Sometimes

- Changing Visitor Behaviour Over Time
 - Data becomes stale
 - It may be gradual
 - Popularity of product may wane
 - This may be abrupt
 - Summer heat-wave, Interest rate changes

■

■

Big Data is not so Big Sometimes

- Changing Visitor Behaviour Over Time
 - Data becomes stale
 - It may be gradual
 - Popularity of product may wane
 - This may be abrupt
 - Summer heat-wave, Interest rate changes
- At some point additional historic data will add more noise than signal

■

Big Data is not so Big Sometimes

- Changing Visitor Behaviour Over Time
 - Data becomes stale
 - It may be gradual
 - Popularity of product may wane
 - This may be abrupt
 - Summer heat-wave, Interest rate changes
- At some point additional historic data will add more noise than signal
- -> Learn from data up to that point and no more

Big Data is not so Big Sometimes

- Learn objective functions that matter to client
 - Revenue rather than click-through
- Changing action set over time
- Changing visitor behaviour over time
-
-
-

Big Data is not so Big Sometimes

- Learn objective functions that matter to client
 - Revenue rather than click-through
- Changing action set over time
- Changing visitor behaviour over time
- Learn rapidly in Proof of Concept implementations
-
-

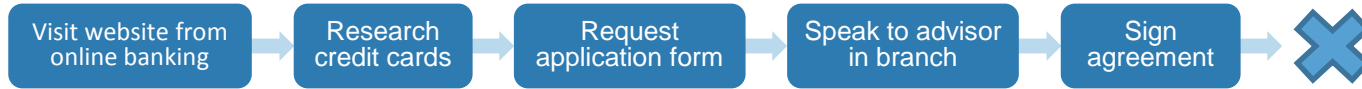
Big Data is not so Big Sometimes

- Learn objective functions that matter to client
 - Revenue rather than click-through
- Changing action set over time
- Changing visitor behaviour over time
- Learn rapidly in Proof of Concept implementations
- Most data is noise
-

Big Data is not so Big Sometimes

- Learn objective functions that matter to client
 - Revenue rather than click-through
- Changing action set over time
- Changing visitor behaviour over time
- Learn rapidly in Proof of Concept implementations
- Most data is noise
- -> smart counting is not sufficient

Concurrent Customer Interactions

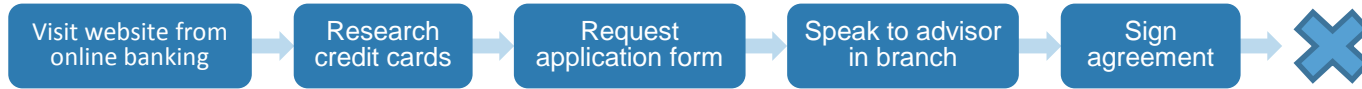


- At any time there are a large number of customer trajectories in progress

-

-

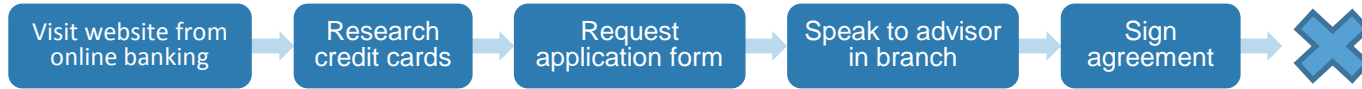
Concurrent Customer Interactions



- At any time there are a large number of customer trajectories in progress
- Time between each interaction is highly variable

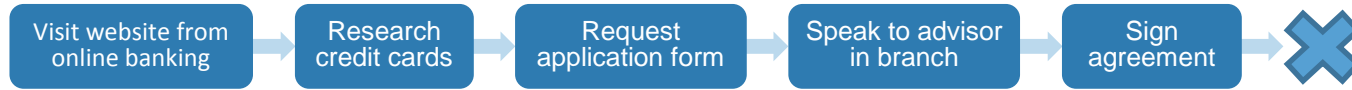
▪

Concurrent Customer Interactions



- At any time there are a large number of customer trajectories in progress
- Time between each interaction is highly variable
- -> Need to avoid long delays to learning

Concurrent Customer Interactions

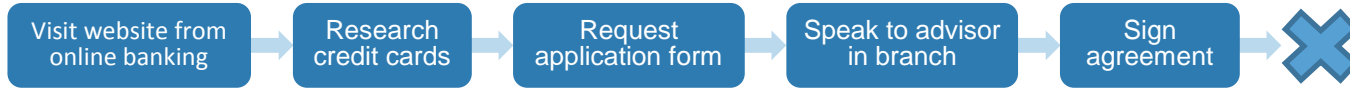


- Need mechanism where:

-

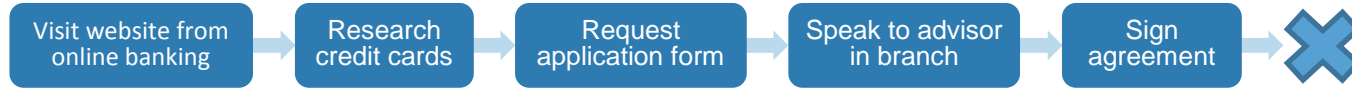
-

Concurrent Customer Interactions



- Need mechanism where:
 - Learning can be transferred as quickly as possible *to other concurrent customers*
 -

Concurrent Customer Interactions



- Need mechanism where:
 - Learning can be transferred as quickly as possible *to other concurrent customers*
 - Without waiting for next interaction or end of sequence

Speed of Learning

- Experience replay
- Regularisation
- Adaptive learning rate, eg IDBD
- Weight initialisation
- Improved Exploration
 - E-greedy
 - Simple but can perform badly when more exploration is required
 - UCB type exploration

Visualisation and Explanation

- How can I trust the system will work?
- What has the system learned?

-

-

-

-

Visualisation and Explanation

- How can I trust the system will work?
- What has the system learned?

- Simple accessible views
 - Not easy with complex internal representation
 -
 -

Visualisation and Explanation

- How can I trust the system will work?
- What has the system learned?

- Simple accessible views
 - Not easy with complex internal representation
- Explanation of why individual decisions are made

-

Visualisation and Explanation

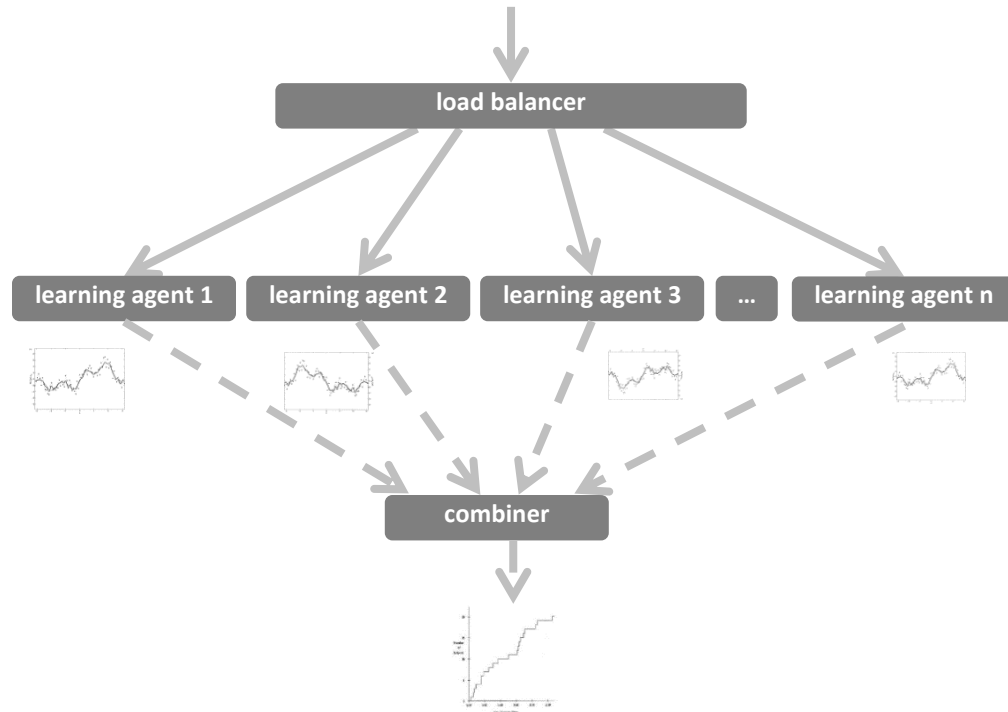
- How can I trust the system will work?
- What has the system learned?

- Simple accessible views
 - Not easy with complex internal representation
- Explanation of why individual decisions are made

- Encourage operator engagement

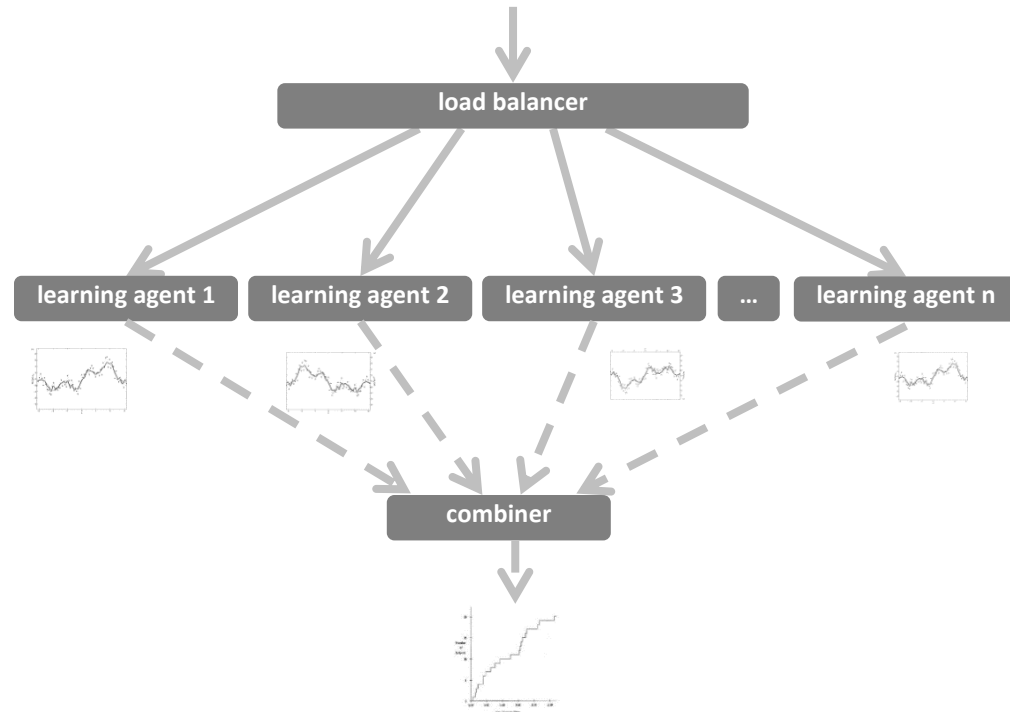
Scalability and Redundancy

- Multiple learning agents



Scalability and Redundancy

- Multiple learning agents
- -> Regular dissemination of learning to other agents





THANK YOU

Leonard Newnham

leonard.newnham@nice.com