Chasing nanoseconds: data science for low latency networks

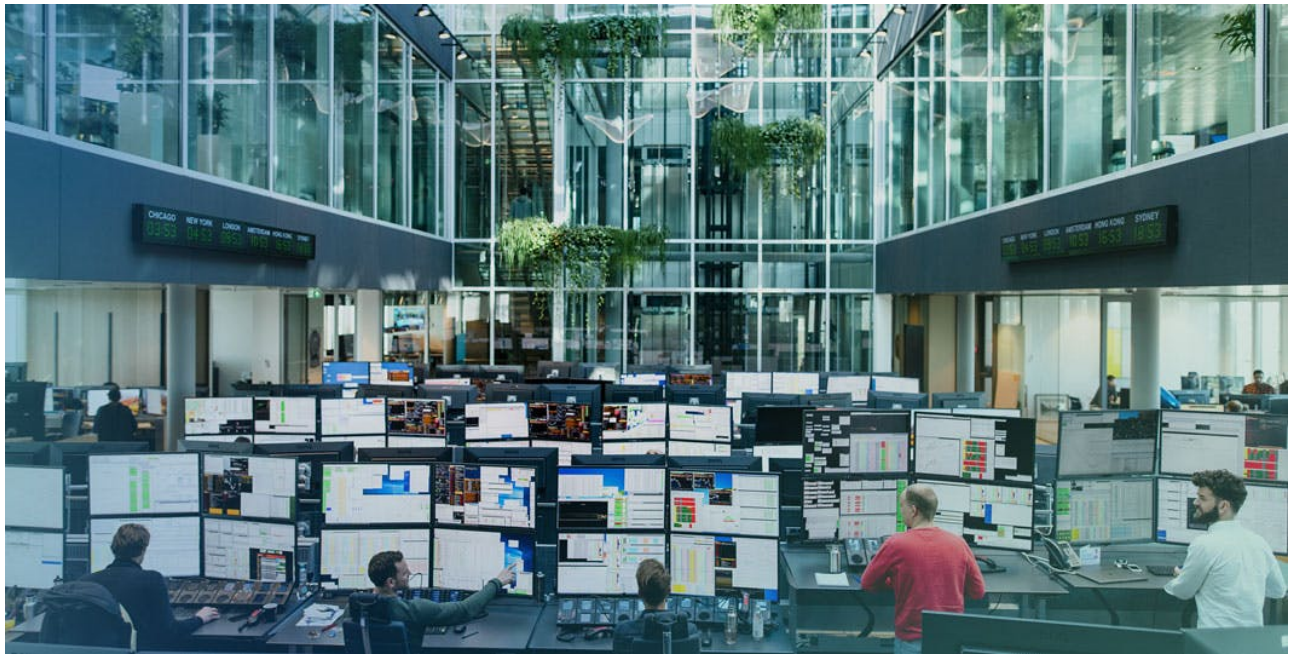
Omer Yuksel, Performance Analyst

IMC Trading

omer.yuksel@imc.com

Introduction - IMC

- Technology-driven trading
- Amsterdam, Chicago, Sydney

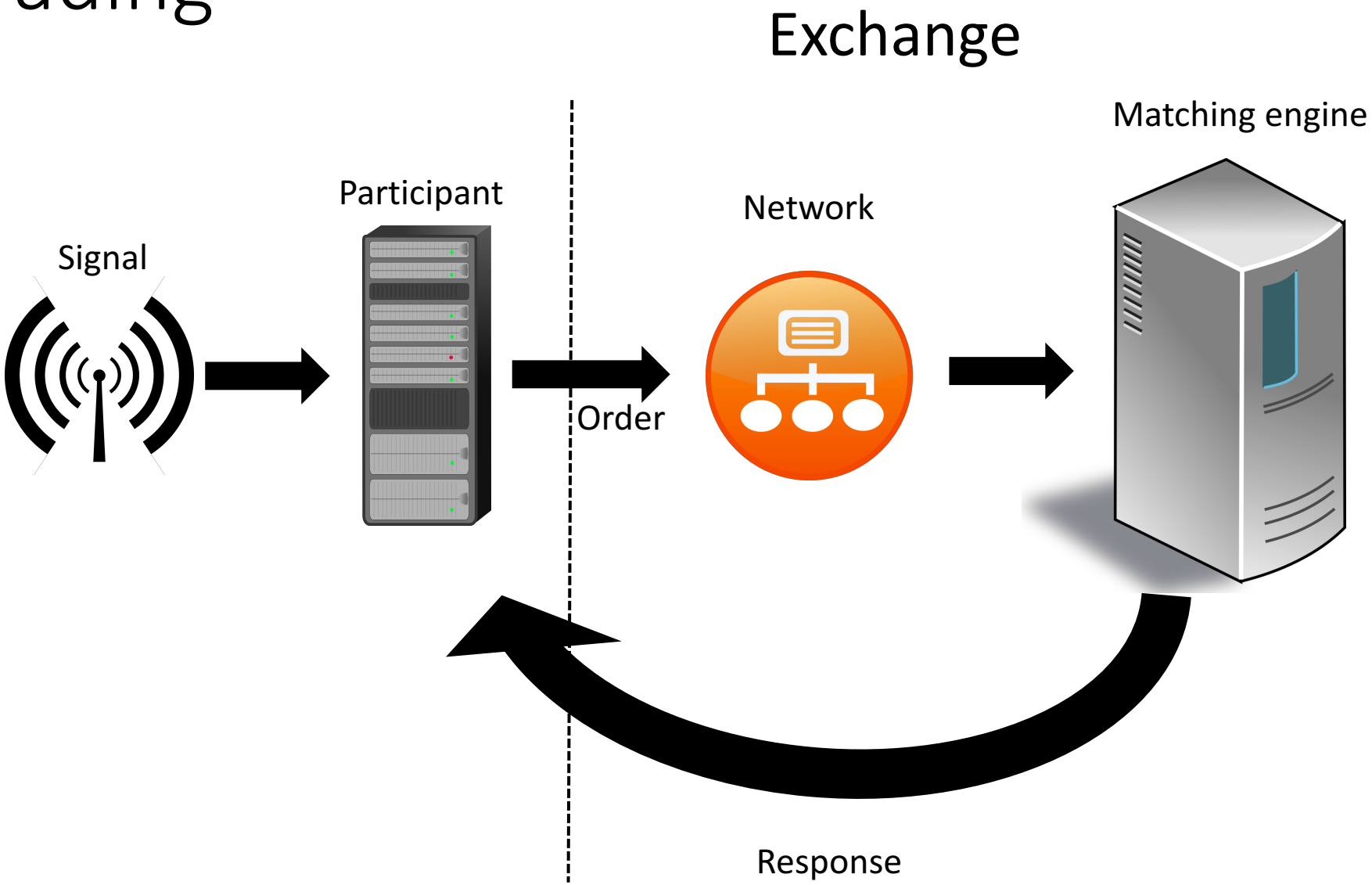


www.imc.com

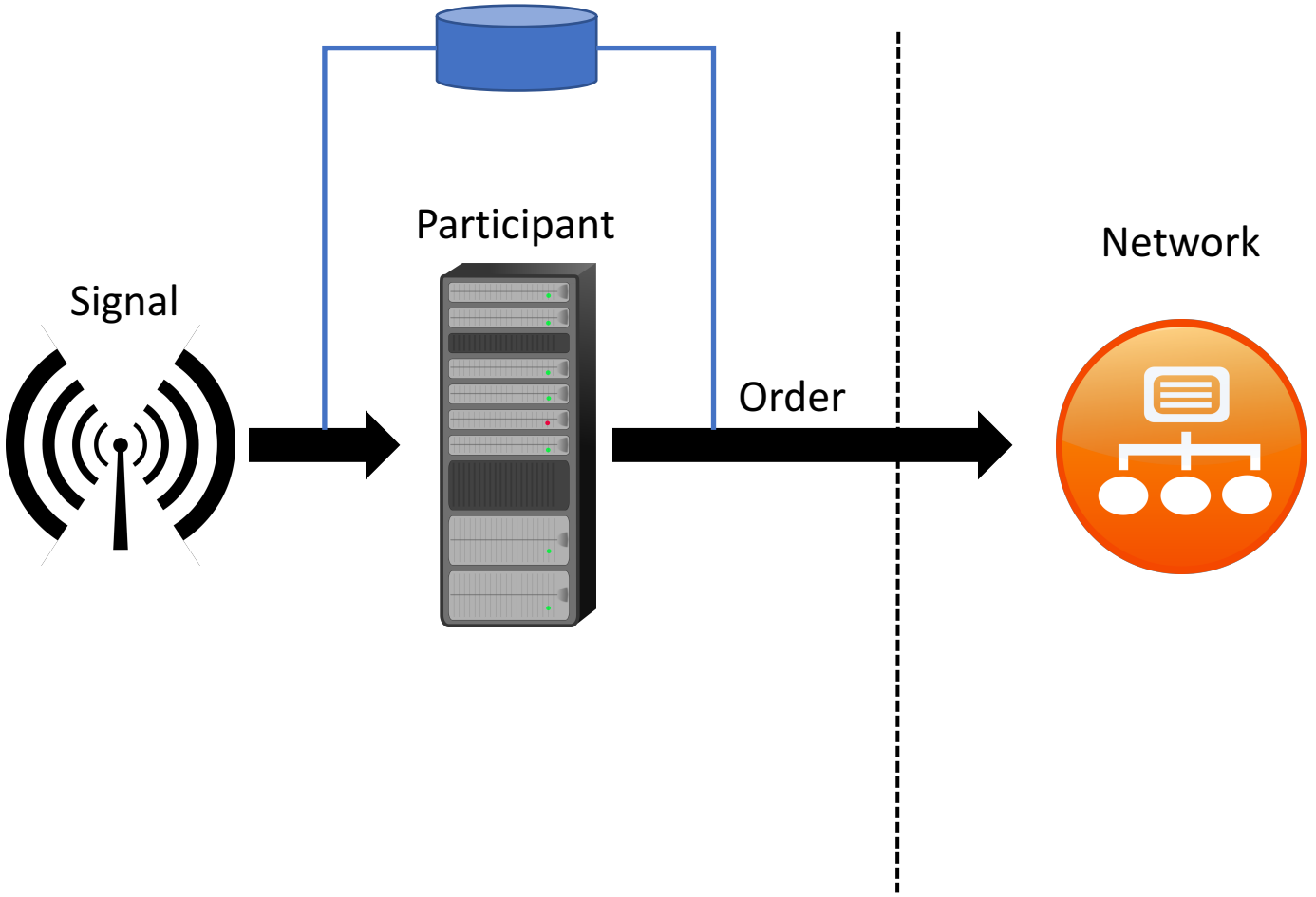
Outline

- Trading loop
- Modelling
- Anomaly Detection
- Challenges and pitfalls

Trading

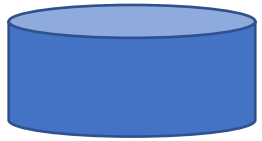

Exchange
Matching engine
Participant
Network
Signal
Order
Response

Reaction Time



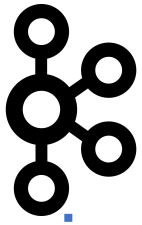
Data pipelines

Capture/Timestamping device



Capture host

Kafka



Raw data

```
0000   00 16 3e ba b7 75 fe 7f   3a e7 ad 1f 08 00 45 c0   ..>..u.. :.....E.
0010   00 97 9e 75 40 00 40 06   81 20 0a 00 03 01 0a 00   ...u@.@. . ......
0020   03 0b d9 64 19 e9 38 81   8a 62 4e f9 e8 c1 80 18   ...d..8. .bN.....
0030   00 3c 1a 95 00 00 01 01   08 0a 00 01 75 90 00 01   .<...... ....u...
```

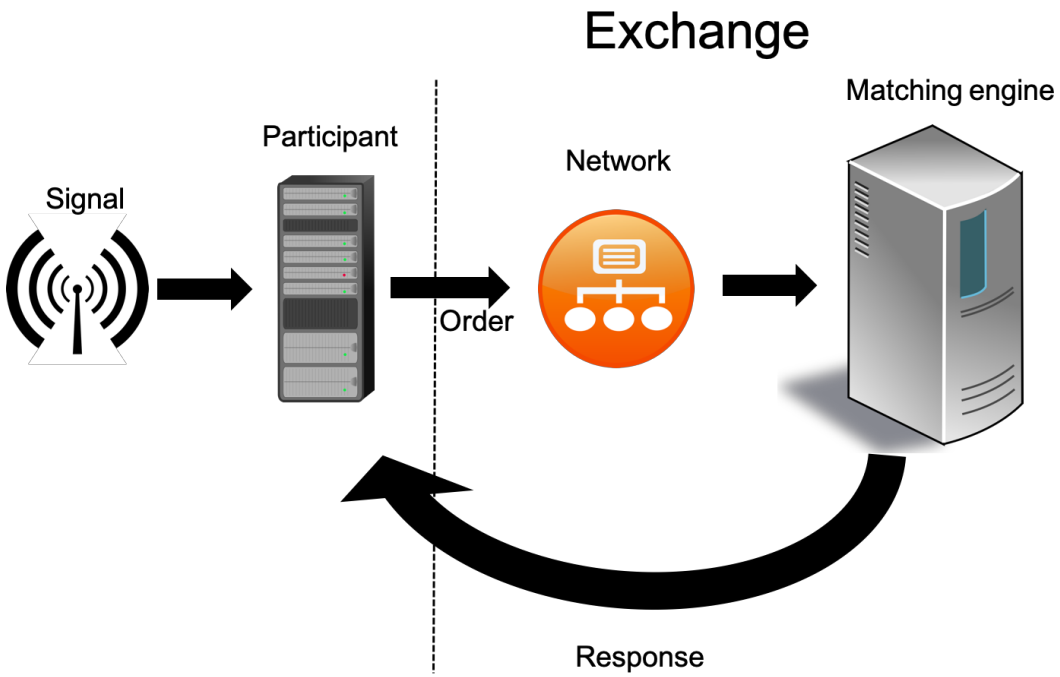
PCAP

```
typedef struct pcaprec_hdr_s {
        guint32 ts_sec;         /* timestamp seconds */
        guint32 ts_usec;        /* timestamp microseconds */
        guint32 incl_len;       /* number of octets of packet saved in file */
        guint32 orig_len;       /* actual length of packet */
} pcaprec_hdr_t;
```

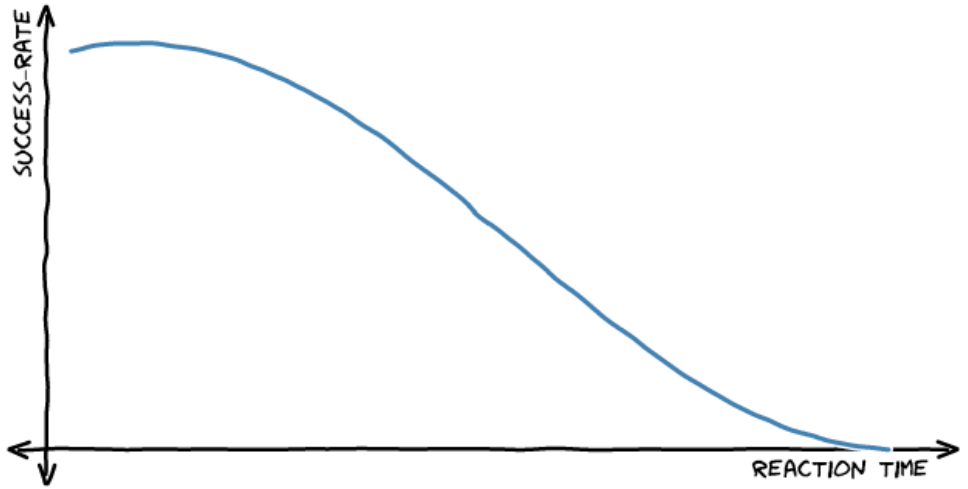
Decoded Message

Storage / Applications

Modelling

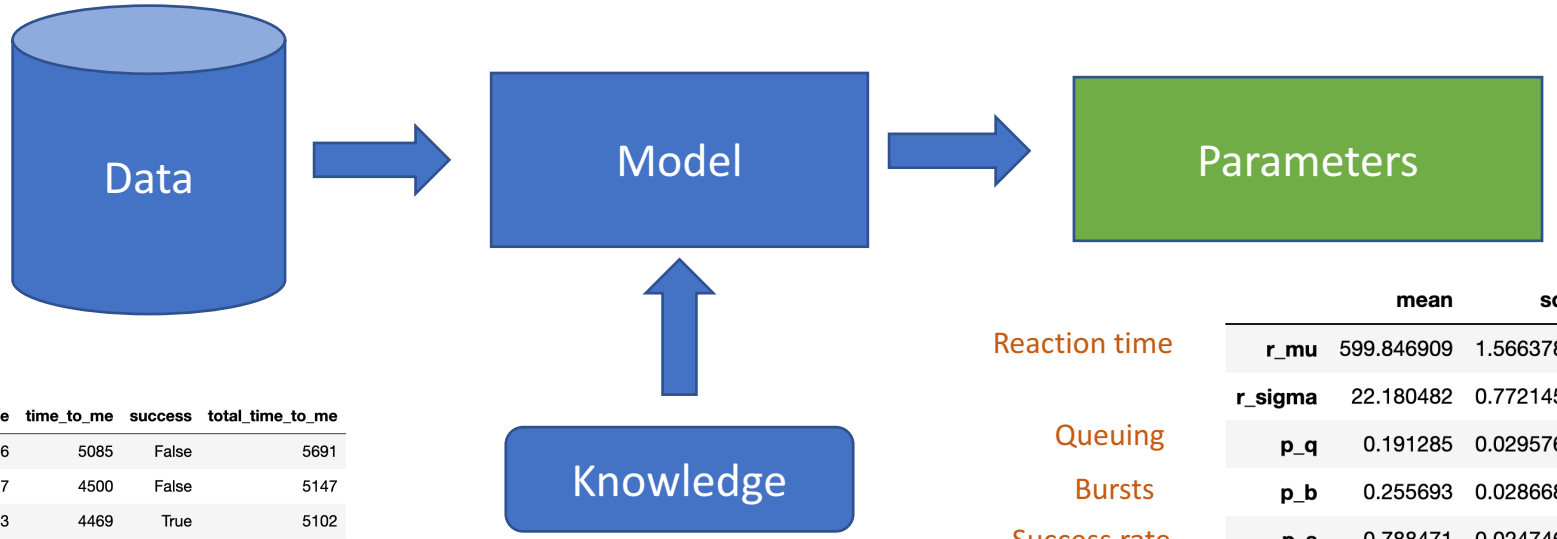


- How often are we queuing?
- How much does queuing matter?
- How much should we improve our reaction time?



https://github.com/omersyuksel/pydata-london-2019

Finding parameters



	ts	reaction_time	time_to_me	success	total_time_to_me
0	2019-06-03 09:00:00.042956193+02:00	606	5085	False	5691
1	2019-06-03 09:00:00.207588123+02:00	647	4500	False	5147
2	2019-06-03 09:00:00.276477343+02:00	633	4469	True	5102
3	2019-06-03 09:00:00.306361141+02:00	577	4459	True	5036
4	2019-06-03 09:00:00.389016054+02:00	599	4349	True	4948
5	2019-06-03 09:00:00.426910915+02:00	578	4515	True	5093
6	2019-06-03 09:00:00.552713100+02:00	572	4472	True	5044
7	2019-06-03 09:00:00.783978162+02:00	566	4680	True	5246
8	2019-06-03 09:00:00.870361884+02:00	606	4457	True	5063
9	2019-06-03 09:00:00.948479263+02:00	563	4394	True	4957

- Minimum queuing delay: 250ns
- Number of switches: 2

Reaction time

Queuing

Bursts

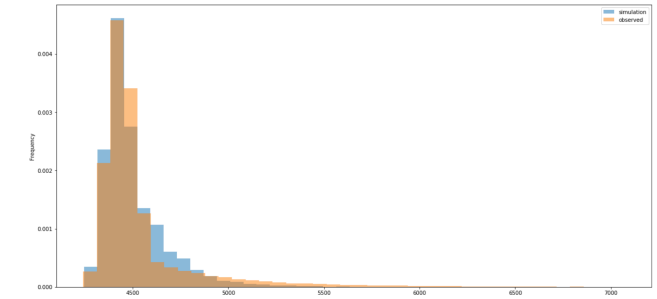
Success rate

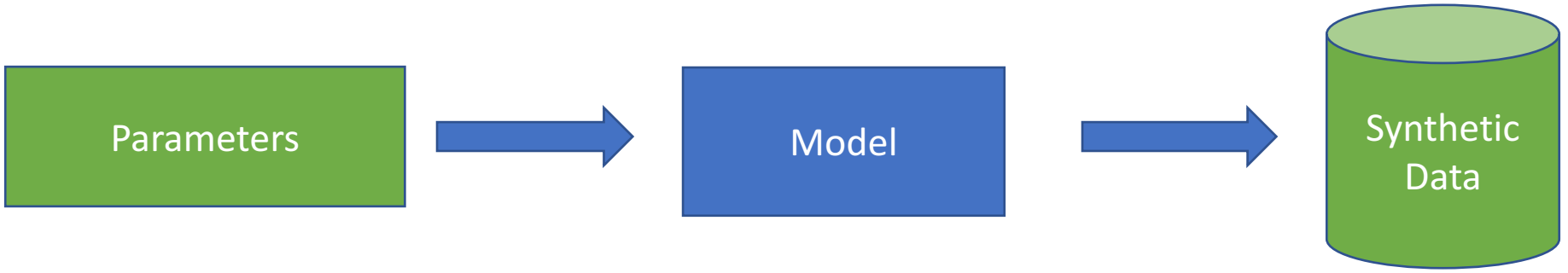
	mean	sd	mc_error	hpd_2.5	hpd_97.5
r_mu	599.846909	1.566378	0.016985	596.739331	602.869329
r_sigma	22.180482	0.772145	0.008591	20.637166	23.673577
p_q	0.191285	0.029576	0.000252	0.135996	0.251843
p_b	0.255693	0.028668	0.000265	0.201732	0.313731
p_s	0.788471	0.024746	0.000210	0.738779	0.835984
p_s_a	0.424210	0.039147	0.000366	0.349996	0.502416

Generating synthetic data

Model validation

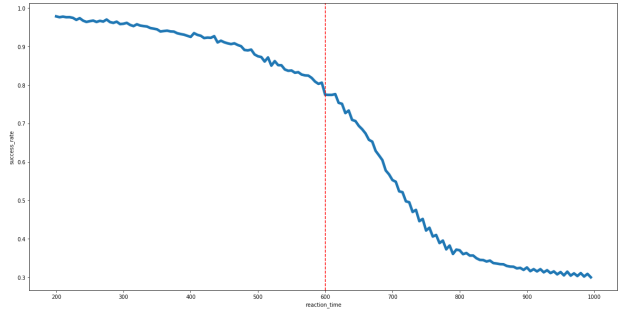
Synthetic vs real data





What-if scenarios

Reaction time vs success rate



Approaches

- Simulate all details
  - SimPy

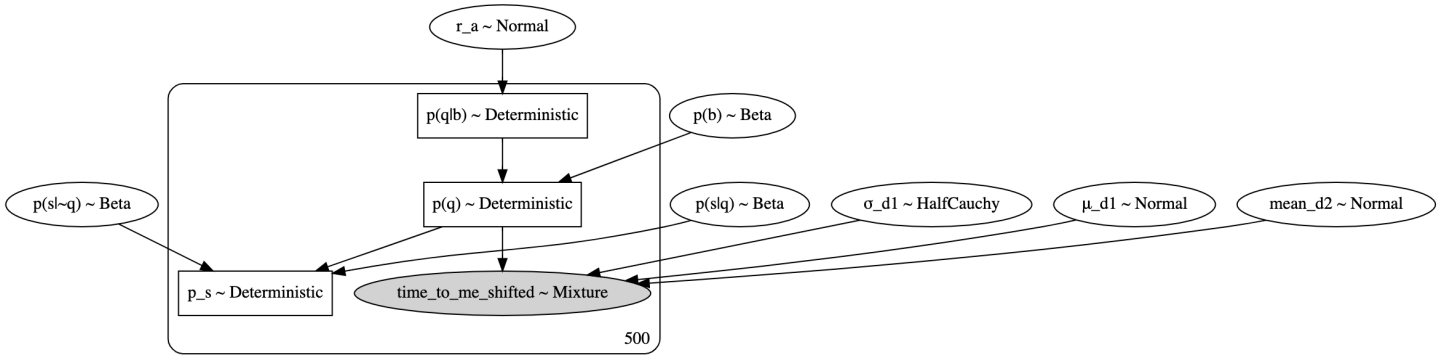
```python
class FIFOSwitch(NetworkNode):
    def __init__(self, name, env, destination, time_to_destination):…

    def run(self):
        while True:
            packet = yield self.incoming_packets.get()
            self.debug(f'{packet} arrived')
            self.env.process(self.process_packet(packet))

    def process_packet(self, packet):
        yield self.env.timeout(SWITCH_PROCESSING_DELAY)
        self.outgoing_packets.put(packet)

    def transmit_outgoing_packets(self):
        while True:
            packet = yield self.outgoing_packets.get()
            self.debug(…)
            self.send_to_destination(packet)
            yield (self.env.timeout(TRANSMISSION_DELAY))
```

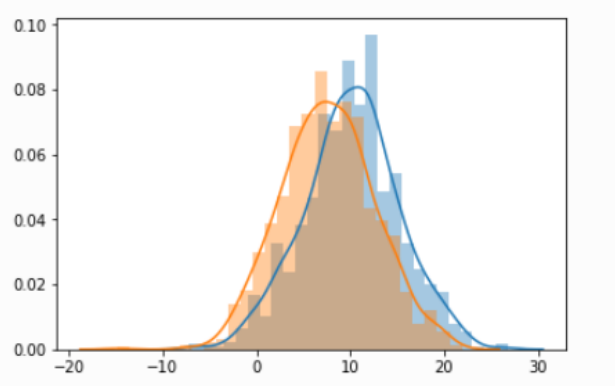
- Formulate as probability distributions
  - PyMC3



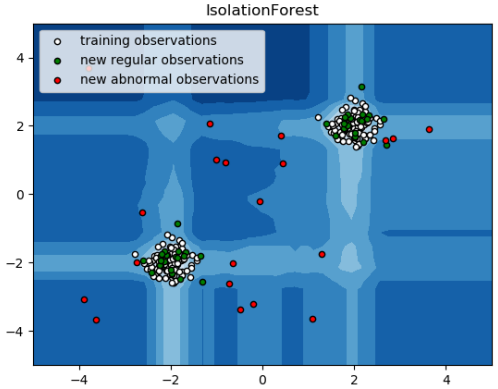
Anomaly Detection

Detecting unusual events without training on prior examples.

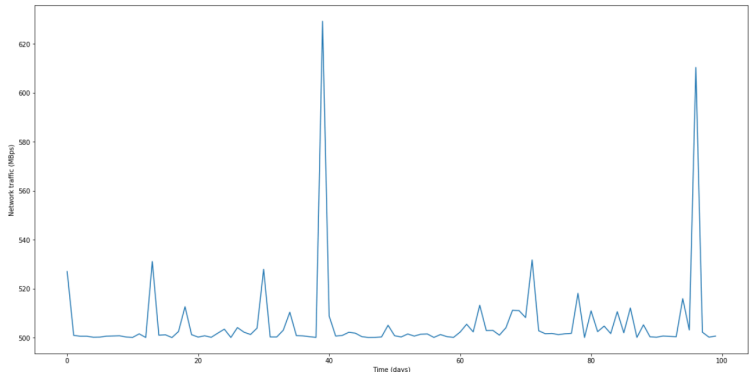
Probabilistic



Machine Learning



Time-series analysis



https://scikit-learn.org/stable/modules/outlier_detection.html#isolation-forest

Anomaly detection at IMC

Centralized

- Domain-agnostic
- 1-dimensional time-series
- Java-based, with Python extensions
- Focus on interpretability and alerting

Customized

- Domain-specific
- Python-based
- Focus on flexibility

Example metrics:

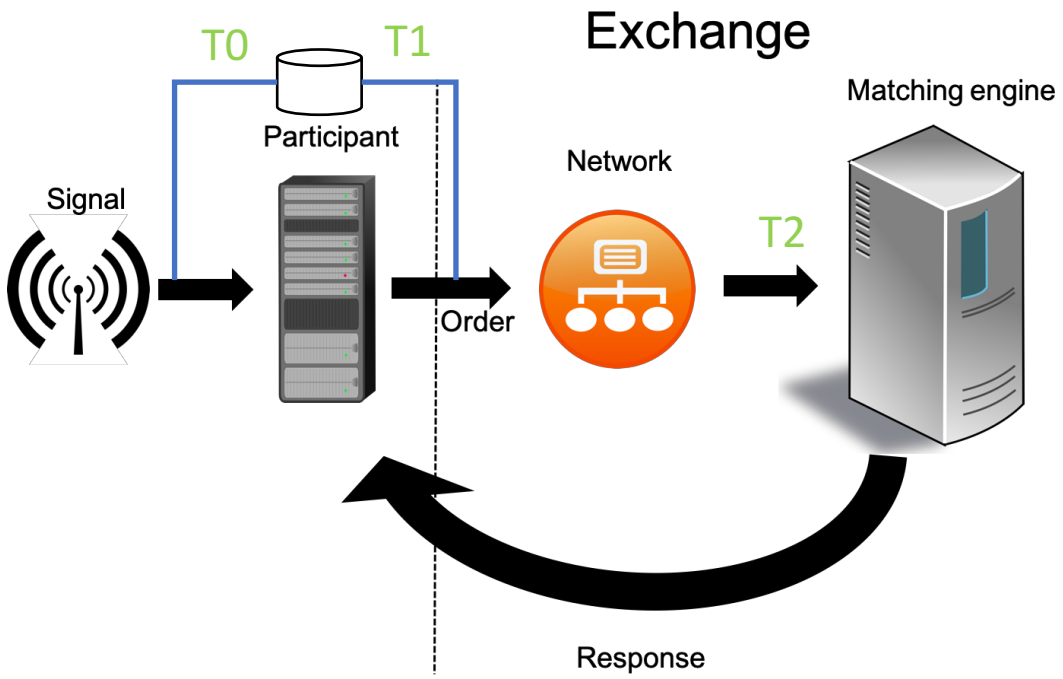
- Reaction time
- Model parameters
- Clock synchronization

Lessons learned

- Preprocessing
- Scaling to organization
- Reporting

What could go wrong?

Sources of noise



- Propagation delay
- Jitter
- Clock synchronization

Using nanosecond timestamps – Pandas (I)

Attempt #1

```
nano_df = pd.read_csv(FILE)
nano_df = nano_df.dropna().astype(int)

nano_df['reaction_time'] = nano_df['t1'] - nano_df['t0']
```

```
nano_df.sample(5)
```

	t0	t1	t2	t3	product_id	quantity	side	reaction_time
98333	1570187623063325440	1570187623063326720	1570187623063338075	1570187623064082201	18	6	1	1280
222264	1570181872005868032	1570181872005869312	1570181872005857293	1570181872005907126	31	5	2	1280
196401	1570192204183381248	1570192204183382528	1570192204183382834	1570192204183438711	3	1	2	1280
59639	1570199323832303104	1570199323832320256	1570199323832267033	1570199323832390999	3	1	2	17152
169307	1570178421201831424	1570178421201832704	1570178421201771461	1570178421201886304	29	3	1	1280

Using nanosecond timestamps – Pandas (II)

```
nano_df.reaction_time.value_counts()
```

```
1280     155871
1536      37902
17152     26768
16896     19845
17408      1487
16640       493
1024        457
17664         2
Name: reaction_time, dtype: int64
```

Using nanosecond timestamps – Pandas (III)

```
In [36]: (nano_df.reaction_time % 256).value_counts()

Out[36]: 0    242825
         Name: reaction_time, dtype: int64

In [37]: (nano_df.t0 % 256).value_counts()

Out[37]: 0    242825
         Name: t0, dtype: int64
```

Float64 storage

- Trade-off precision vs range
- Float64 data type: sign bit, 53 bits mantissa, 11 bits exponent
- Bits required to represent nanosecond timestamps now: 61

Load as object

```
nano_df = pd.read_csv(FILE, dtype='object')
nano_df = nano_df.dropna().astype(int)

nano_df['reaction_time'] = nano_df['t1'] - nano_df['t0']
```

```
nano_df.reaction_time.value_counts().sort_values()
```

```
17352       1
1437        1
17393       1
17392       1
17431       1
          ...
1334     2588
1331     2601
1326     2603
1332     2606
1327     2639
Name: reaction_time, Length: 918, dtype: int64
```

Load as nullable int (I)

```
nano_df = pd.read_csv(FILE, dtype={'t0': 'Int64', 't1': 'Int64'})

nano_df['reaction_time'] = nano_df['t1'] - nano_df['t0']

nano_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344949 entries, 0 to 344948
Data columns (total 8 columns):
t0               242825 non-null Int64
t1               242825 non-null Int64
t2               344949 non-null int64
t3               344949 non-null int64
product_id       344949 non-null int64
quantity         344949 non-null int64
side             344949 non-null int64
reaction_time    242825 non-null Int64
dtypes: Int64(3), int64(5)
memory usage: 22.0 MB
```

Load as nullable int (II)

```
nano_df.sample(5)
```

	t0	t1	t2	t3	product_id	quantity	side	reaction_time
184304	1570191755423981568	1570191755423998720	1570191755424178135	1570191755424253187	18	4	2	17152
171517	1570194430324996864	1570194430324998144	1570194430325009103	1570194430325807014	31	8	1	1280
39583	1570205505659457280	1570205505659458560	1570205505659300139	1570205505659462984	57	1	1	1280
229145	1570195867805028864	1570195867805030144	1570195867805055969	1570195867805143056	18	1	2	1280
126857	NaN	NaN	1570188729057005056	1570188729057072034	31	3	1	NaN

```
(nano_df['reaction_time'] % 256).value_counts()
```

```
0    242825
Name: reaction_time, dtype: int64
```

Use converters – np.int64

```
def convert_to_int64(x):
  try:
    return np.int64(x)
  except ValueError:
    return 0


nano_df = pd.read_csv(FILE, converters={'t0': convert_to_int64, 't1': convert_to_int64})
nano_df = nano_df.query('t1>0 and t0>0')
nano_df['reaction_time'] = nano_df['t1'] - nano_df['t0']
```

```
nano_df.reaction_time.value_counts().sort_values()
```

```
17352       1
1437        1
17393       1
17392       1
17431       1
          ...
1334     2588
1331     2601
1326     2603
1332     2606
1327     2639
Name: reaction_time, Length: 918, dtype: int64
```

Using datetime type with lower precision

- Javascript: 54-bit timestamps
- Millisecond precision

How to retain nanosecond precision?

Retaining nanosecond precision

- Workaround #1: Cast to string for visualization purposes
- Workaround #2: try to map time of the day to 54-bit timestamps

Retaining nanosecond precision

```
t_int = 15701973325975613 28
```

```
pd.to_datetime(t_int)
```

```
Timestamp('2019-10-04 13:55:32.597561328')
```

```
t_int_day = (t_int % (24*3600*10**9)) # Drop date
```

```
t_int, t_int_day
```

```
(15701973325975613 28, 50132597561328)
```

```
np.log2(t_int), np.log2(t_int_day)
```

```
(60.44565158738884, 45.51081422113211)
```

Retaining nanosecond precision

Converting t_int to datetime64 and t_int_day to datetime in milliseconds:

t_int: 2019-10-04 13:55:32.597561328 1570197332597561328

t_int_day: 3558-08-22 11:32:41.328 50132597561328

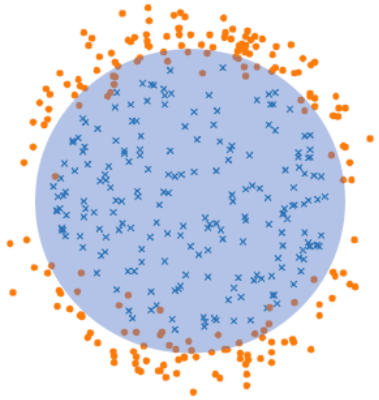
Conversion table

Micro	Actual
Milliseconds	1 ns
Seconds	1 us
Minutes	60 us
Hours	3.6 ms
Days	86.4 ms
Months	~2.5 seconds
Years	~30 seconds
Centuries	~8 hours

Questions?

Classification vs Anomaly Detection

Classification



Anomaly detection