Data Science Project



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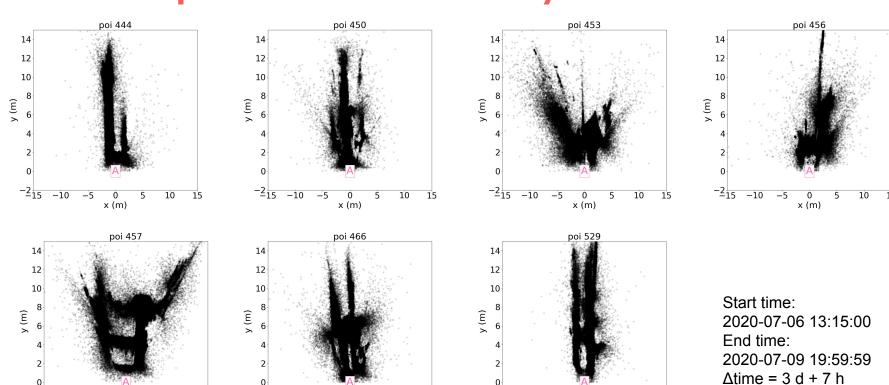
Business Problem

Improve Smart Signage & Targeting



Data Exploration - Store Layouts

10

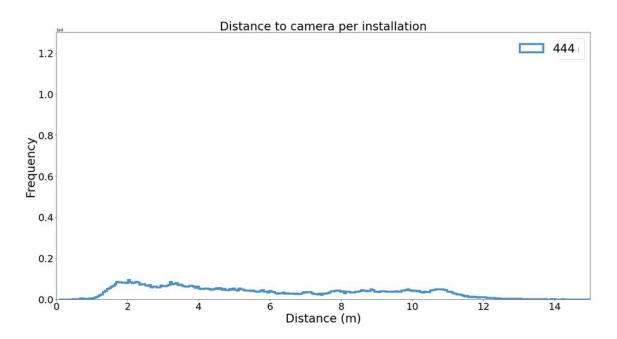


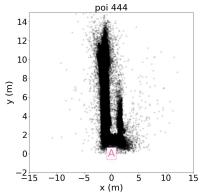
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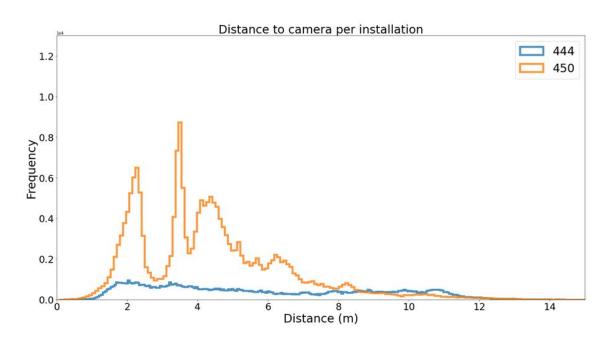
x (m)

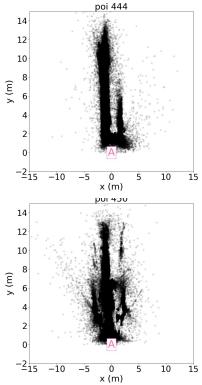
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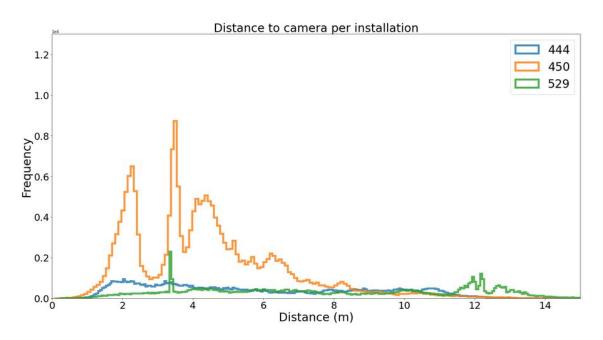
x (m)

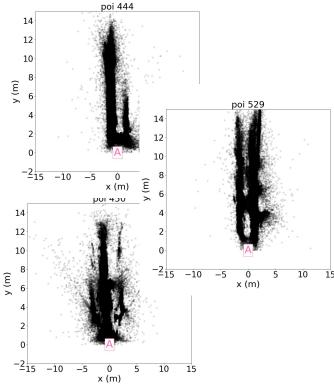


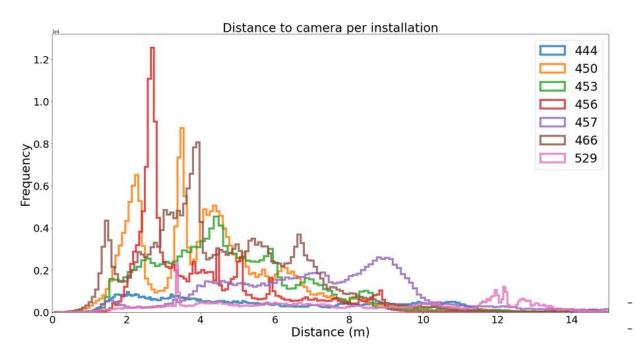


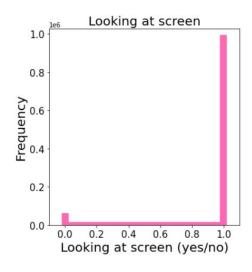












N/A head position - 25% of data Looking at screen - 4% of 75%

Data Engineering

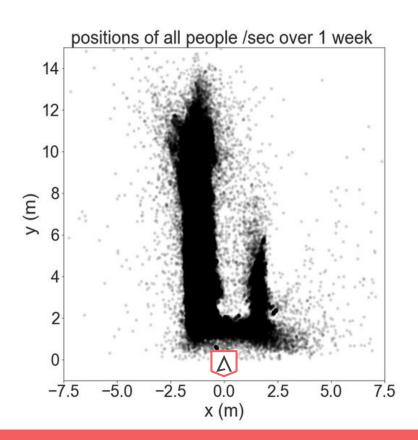
Data imbalance

- Predicting attention: only 4% of person_looking
- Predicting presence: 1, 2, 5 seconds prediction windows

Engineering

- Outlier and error removal
- Added features: exponential moving averages, velocity, cumulative time, distance to camera
- Data format: ms -> sec created some duplicate timestamps needing adjusting
- Missing data: linearly extrapolated
- Age/Gender rolling estimate

Customer Trajectory & Store Layout



Predict Presence

For 85 people out of 100 we can accurately predict if person will leave within the 5 sec

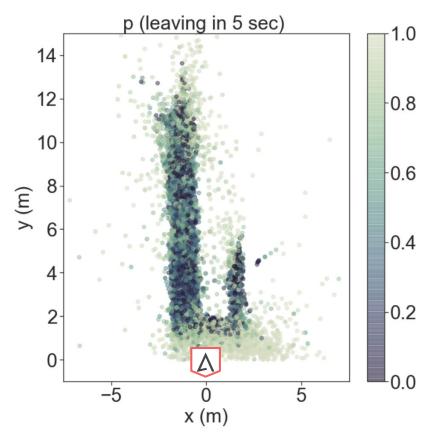


Illustration of one installation with 5-second predictive time window

Predict Presence - Modeling Results

| Predict presence (1/0) in n seconds | | | | | | | | | |
|-------------------------------------|-------------|-----------|--------|-----------|--------|-----------|--------|--|--|
| Predictive window | | 5 sec | | 2 sec | | 1sec | | | |
| Approach | KPI | Precision | Recall | Precision | Recall | Precision | Recall | | |
| keep every 2nd row | 0 - absent | 83 | 64 | 75 | 52 | 63 | 32 | | |
| Reep every Zhu Tow | 1 - present | 84 | 87 | 92 | 96 | 94 | 98 | | |
| keep every 5th row | 0 - absent | 87 | 78 | 75 | 54 | 63 | 34 | | |
| keep every surrow | 1 - present | 75 | 71 | 87 | 93 | 91 | 97 | | |
| data balance 50/50 | 0 - absent | 85 | 84 | 85 | 83 | 83 | 86 | | |
| uata balance 50/50 | 1 - present | 84 | 85 | 84 | 85 | 85 | 83 | | |

Precision: For 100 customers that we predict will be present in 5 sec, 16 have already left.

Recall: For 100 customers that will be present in 5 sec, we only predicted 85, i.e. we missed 15.

Predict Presence - Modeling Results + Data Imbalance

| Predict presence (1/0) in n seconds | | | | | | | | | |
|-------------------------------------|-------------|-----------|--------|-----------|--------|-----------|--------|--|--|
| Predictive window | | 5 sec | | 2 sec | | 1sec | | | |
| Approach | KPI | Precision | Recall | Precision | Recall | Precision | Recall | | |
| keep every 2nd row | 0 - absent | 83 | 64 | 75 | 52 | 63 | 32 | | |
| Reep every Zild Tow | 1 - present | 84 | 87 | 92 | 96 | 94 | 98 | | |
| keep every 5th row | 0 - absent | 87 | 78 | 75 | 54 | 63 | 34 | | |
| keep every surrow | 1 - present | 75 | 71 | 87 | 93 | 91 | 97 | | |
| data balance 50/50 | 0 - absent | 85 | 84 | 85 | 83 | 83 | 86 | | |
| | 1 - present | 84 | 85 | 84 | 85 | 85 | 83 | | |

| Data Imbalance per Approach | | | | | | |
|-----------------------------|--------------------|-------|-------|------|--|--|
| Predictive | window | 5 sec | 2 sec | 1sec | | |
| 0s in the dataset | No rebalacing | 22% | 9% | 5% | | |
| | Keep every 5th row | 36% | 15% | 7% | | |
| | Keep every 2nd row | 58% | 24% | 12% | | |
| | 50/50 split | 50% | 50% | 50% | | |

Predict Position

Mean position prediction accuracy

In 1 second: 17cm

In 2 seconds: 68cm

In 5 seconds: 134cm

Up to 40% better accuracy (depending on layout)

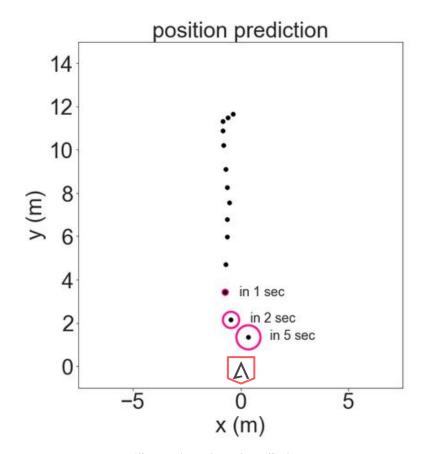


Illustration of one installation

Predict Position - Modeling Results

| (x,y) position prediction | | | | | | | |
|---------------------------|----------|-----------|-----------|--|--|--|--|
| Timeframe | 1 second | 2 seconds | 5 seconds | | | | |
| POI \ KPI | RMSE | RMSE | RMSE | | | | |
| 450 | 0.12 | 0.44 | 0.85 | | | | |
| 466 | 0.14 | 0.51 | 0.92 | | | | |
| 444 | 0.15 | 0.56 | 1.10 | | | | |
| 456 | 0.16 | 0.54 | 1.15 | | | | |
| 453 | 0.16 | 0.78 | 1.63 | | | | |
| 457 | 0.20 | 0.81 | 1.67 | | | | |
| 529 | 0.23 | 1.14 | 2.07 | | | | |
| Mean | 0.17 | 0.68 | 1.34 | | | | |

Physical store layout impacts the prediction error

Predict Position - Modeling Results

| (x,y) position prediction | | | | | | | |
|---------------------------|----------|----------|------|----------|-----------|----------|--|
| Timeframe | 1 second | | 2 se | conds | 5 seconds | | |
| POI \ KPI | RMSE | d(ŷ - y) | RMSE | d(ŷ - y) | RMSE | d(ŷ - y) | |
| 529 | 0.23 | 0.12 | 1.14 | 0.62 | 2.07 | 1.61 | |
| 466 | 0.14 | 0.05 | 0.51 | 0.28 | 0.92 | 0.74 | |
| 457 | 0.20 | 0.11 | 0.81 | 0.58 | 1.67 | 1.57 | |
| 456 | 0.16 | 0.06 | 0.54 | 0.35 | 1.15 | 0.96 | |
| 453 | 0.16 | 0.08 | 0.78 | 0.50 | 1.63 | 1.34 | |
| 450 | 0.12 | 0.05 | 0.44 | 0.26 | 0.85 | 0.67 | |
| 444 | 0.15 | 0.08 | 0.56 | 0.37 | 1.10 | 0.98 | |
| Mean | 0.17 | 0.08 | 0.68 | 0.42 | 1.34 | 1.12 | |

Delta (ŷ - y): distance between actual position and prediction, in meter

Predict Attention

For 7 people out of 10 we can accurately predict if person will look at the screen within the next few seconds

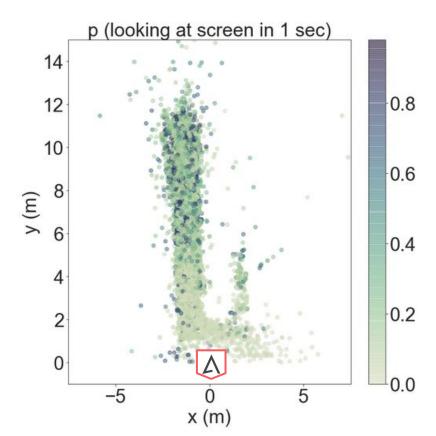


Illustration of one installation with 1-second predictive time window

Predict Attention - Modeling Results

| Predict Attention to Screen in n seconds | | | | | | | | |
|--|---|-----------|--------|-----------|--------|-----------|--------|--|
| Predictive window | | 5 sec | | 2 sec | | 1 sec | | |
| KPI | | Precision | Recall | Precision | Recall | Precision | Recall | |
| Not Looking | 0 | 0.9 | 0.94 | 0.84 | 0.93 | 0.72 | 0.83 | |
| Looking | 1 | 0.68 | 0.42 | 0.68 | 0.39 | 0.66 | 0.46 | |

Precision: For 100 customers that we predict will be looking at the screen

in 5 sec, 32 actually will not.

Recall: For 100 customers that will be looking at the screen in 5 sec,

we predicted only 42, i.e. we missed 58 by tagging them as not looking.

Potential Next Steps

Implementation & fine-tuning of Machine Learning models

Further exploration of **Deep Learning** models

Add **product position information** for improved targeting



Thank you!



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