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Simple Touch Prediction With Built-In IMUs

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Smartphone sizes are increasing steadily.

Whole front screen can not be reached without changing the grip.

Predict where users want to touch.



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Preload content based on future touch.

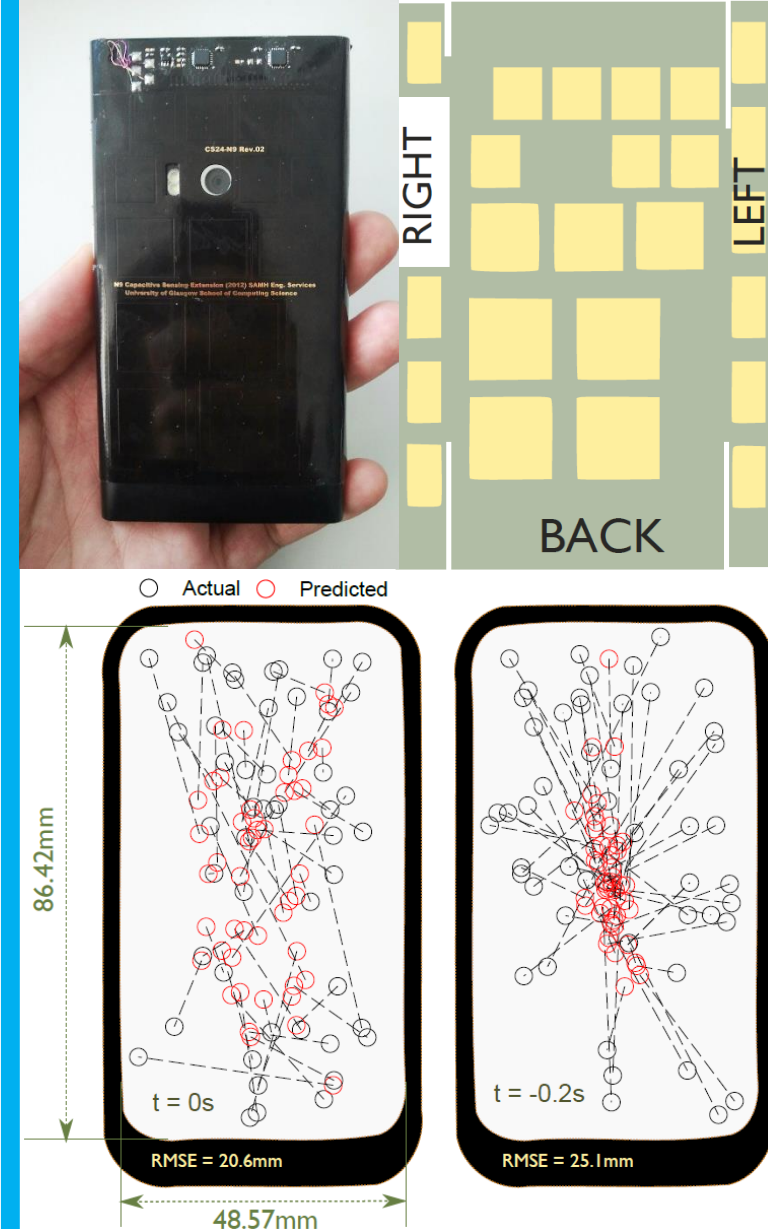
Enhance content for further information gathering.



28 Frames Later

Predicting Screen Touches
From Back-of-Device Grip Changes

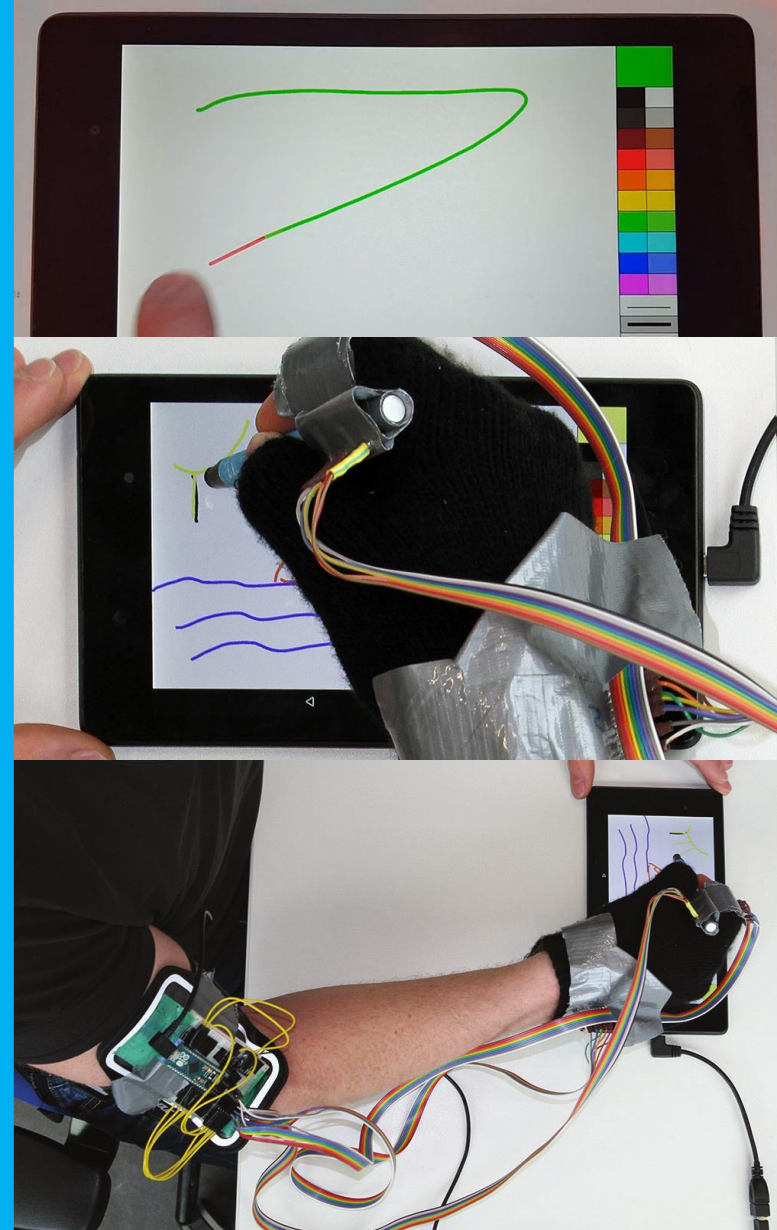
- Analyze grip change with 24 sensors on the phones' laterals and back side
- Predict future touch positions
- Achievement of an accuracy of 18 mm and predicting touches 200ms in the future



PredicTouch

Reducing Touchscreen Latency using Neural Nets

- Reduce perceivable touchscreen latency by predicting future positions on touchscreen
- Neural network combines IMU data with touch trajectories to predict future trajectories
- Predicting 66ms into the future increases users' throughput by 15% and 17% for finger and stylus



New Approach

Use IMU data to predict future touches.

IMUs are better suited for ordinary usage than additional sensors.

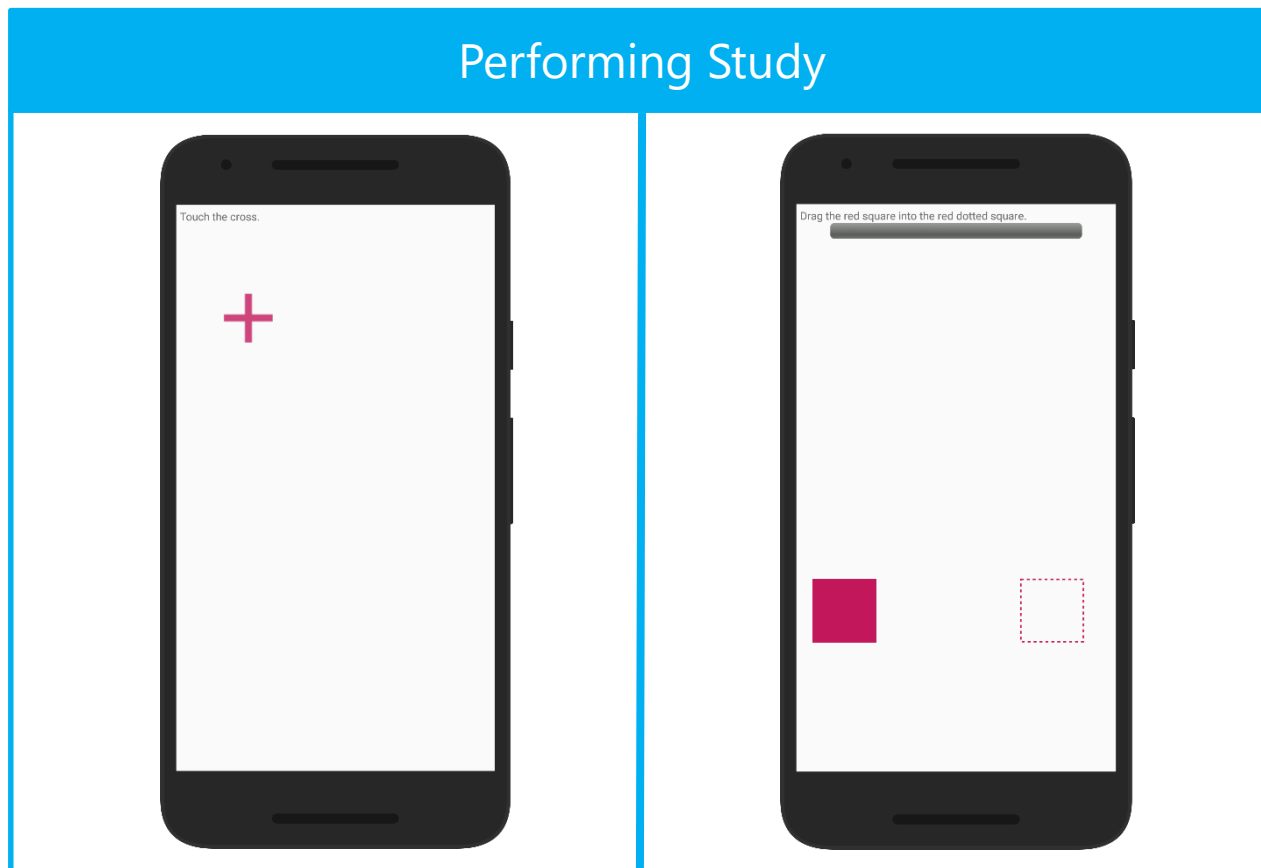
Suitability in natural environments.

Drive development for accuracy.



Design

- Repeated-measures design
- 1 independent variable: PHONE
- Amount of conditions = 4



Study

- 20 right-handed participants (5 female)
- Aged 21 to 27 (M = 24.25, SD = 1.58)
- Hand lengths 16.0cm to 21.3cm
(M = 19.3cm, SD = 1.47cm)
- Performing 432 touches on 4 phones
 $432 * 4 * 20 = 34.560$ touches
- Sampling IMU data during study
- Duration was 54 minutes on average



Preprocessing

Raw data

Remove duplicates

Resample to 1 sample/3ms

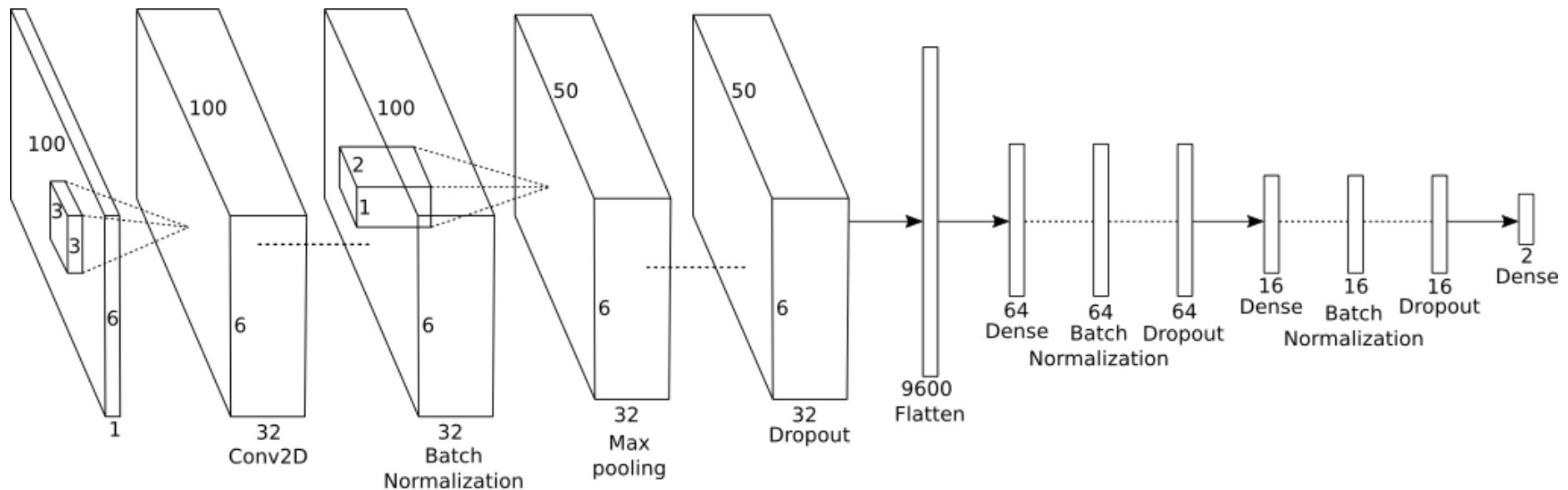
Create intervals with 100 samples before touch

Export dataframe with sensor and touch data

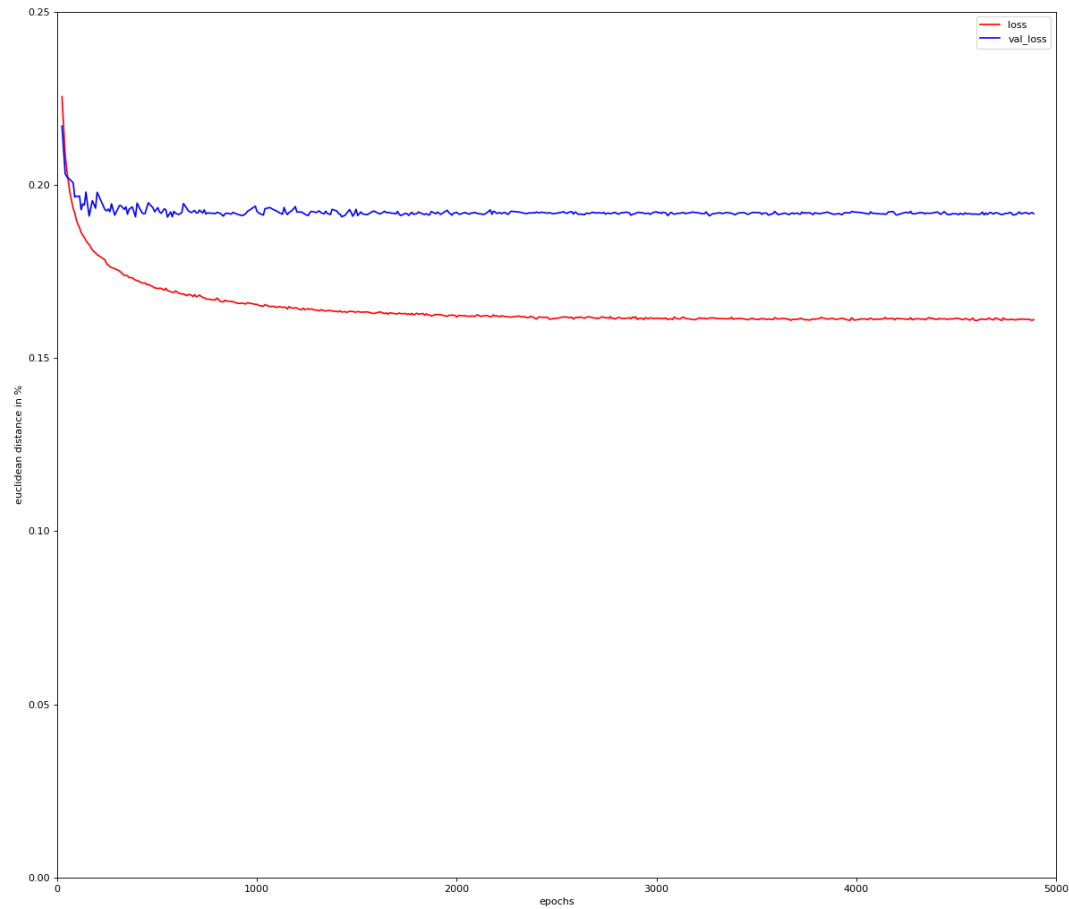
Baseline – Euclidean Distance

Regressor	Random Forest	DecisionTree	KNeighbors	MLP
General (%)	0.382	0.381	0.394	0.41
S3 Mini	28.11mm	28.81mm	28.67mm	30.13mm
S4	34.65mm	35.58mm	34.61mm	36.55mm
Nexus 5X	36.22mm	37.03mm	36.36mm	38.72 mm
Nexus 6	41.27mm	42.55mm	42.91mm	45.29mm

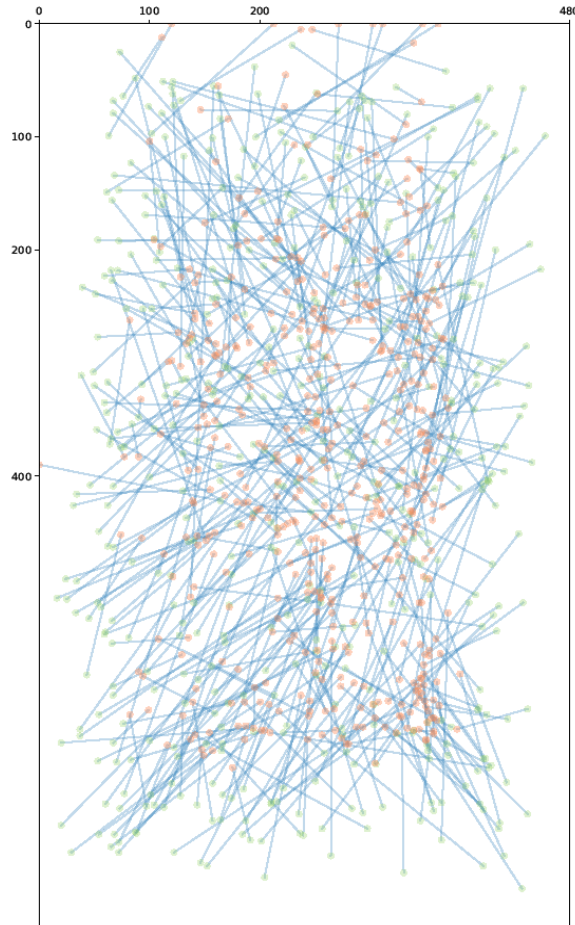
Model Structure



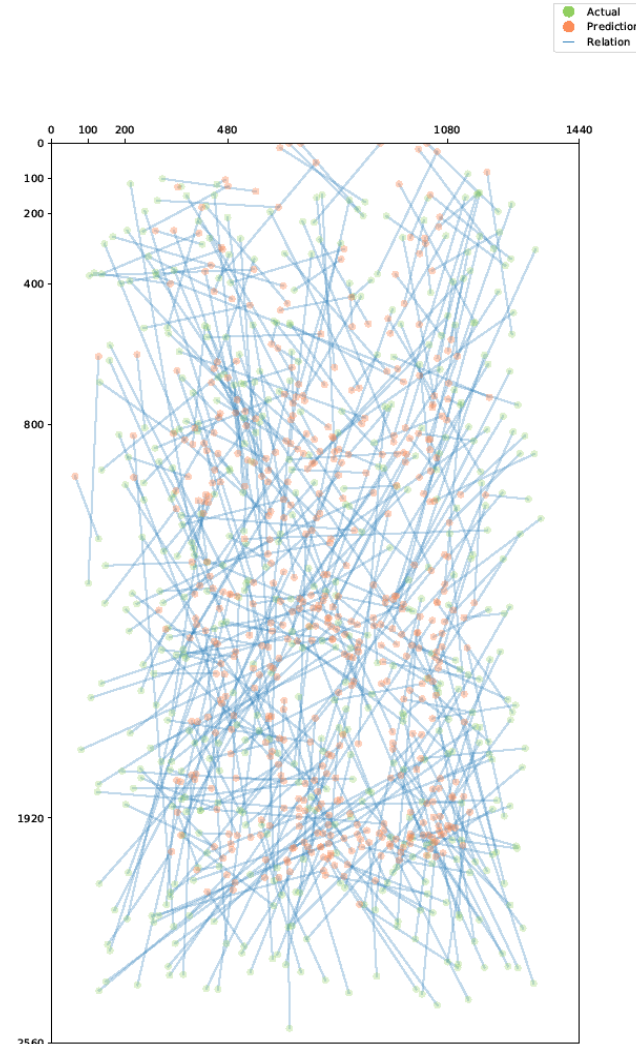
General Model Training



Model Predictions

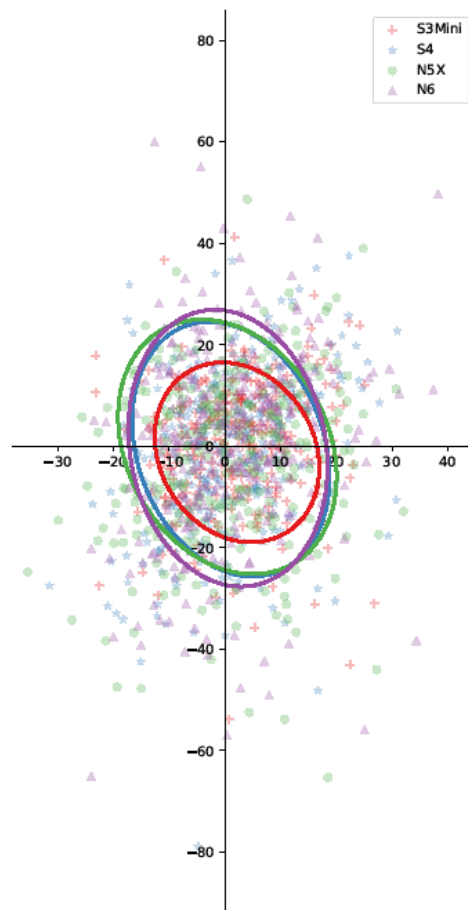


S3 Mini

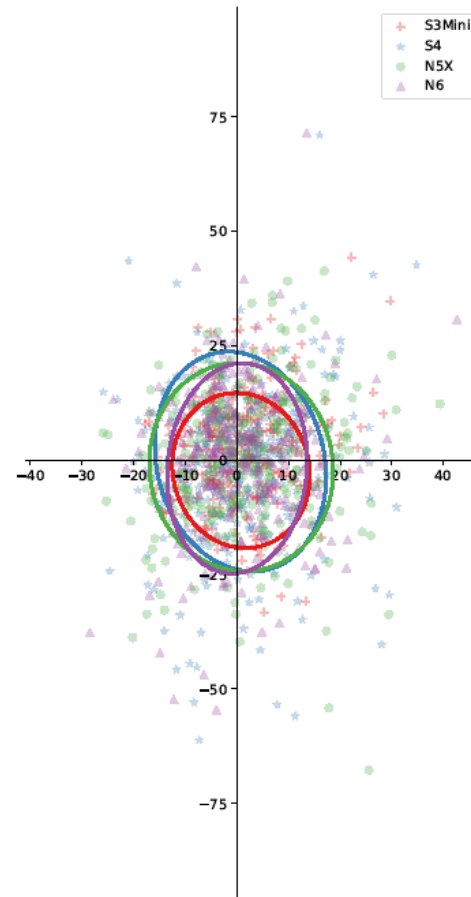


Nexus 6

Model Predictions



General Model



Single Models

Cross Validation

Phone Metric(mm)	S3 Mini	S4	Nexus 5X	Nexus 6
Euclidean Distance	12.56 (6.79)	15.77 (9.18)	16.94 (9.52)	16.98 (10.56)
RMSE	8.88 (4.8)	11.15 (6.49)	11.98 (6.73)	12.01 (7.47)
X-Error	1.64 (8.9)	1.47 (10.57)	1.81 (11.76)	2.23 (10.72)
Y-Error	2.58 (10.53)	3.36 (14.09)	3.94 (14.54)	3.73 (16.1)

Conclusion

- Training a model on sensor values from all phones results in good values.
- However training models on a single phones' sensor values results in slightly better values.
- Reducing the feature space to only accelerometer and gyroscope values produces better results.

Future Work

- Generate a bigger dataset
 - Long term study over one week with about 10 participants
 - Record all sensor values while screen is unlocked
 - Record all touches
- Create interaction methods
- Measure throughput with and without touch prediction

Takeaway

Using IMUs to predict future touches is feasible.

Not all sensors contribute to good results.

Touch prediction on smartphones will enhance interaction possibilities.

