Ubiquitous and Mobile Computing

CS 528: Beyond Location Check-ins: Exploring Physical and Soft Sensing to Augment Social Check-in Apps

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Beyond Location Check-ins: Exploring Physical and Soft Sensing to Augment Social Check-in Apps

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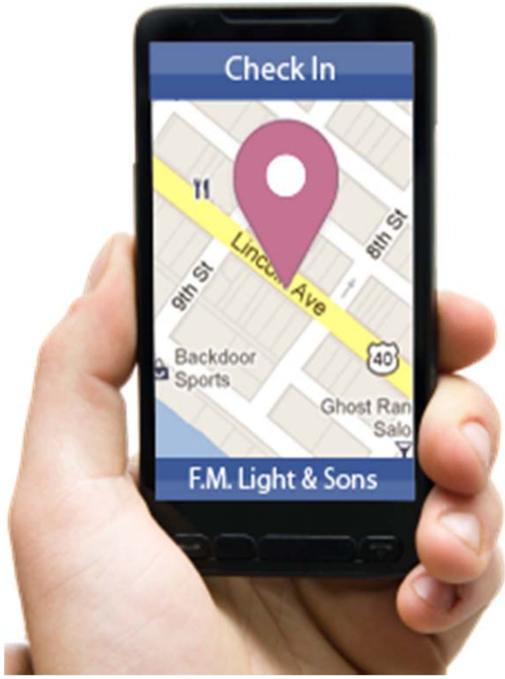
- CONCLUSION

introduction

- expand the spectrum of information that can be shared with friends
- check-in not only location but activities such as eating, coffee, walking ..etc
- **Predicted** and **Suggested** activities ease the check-in process
- mainly use **Software Sensors** to save power

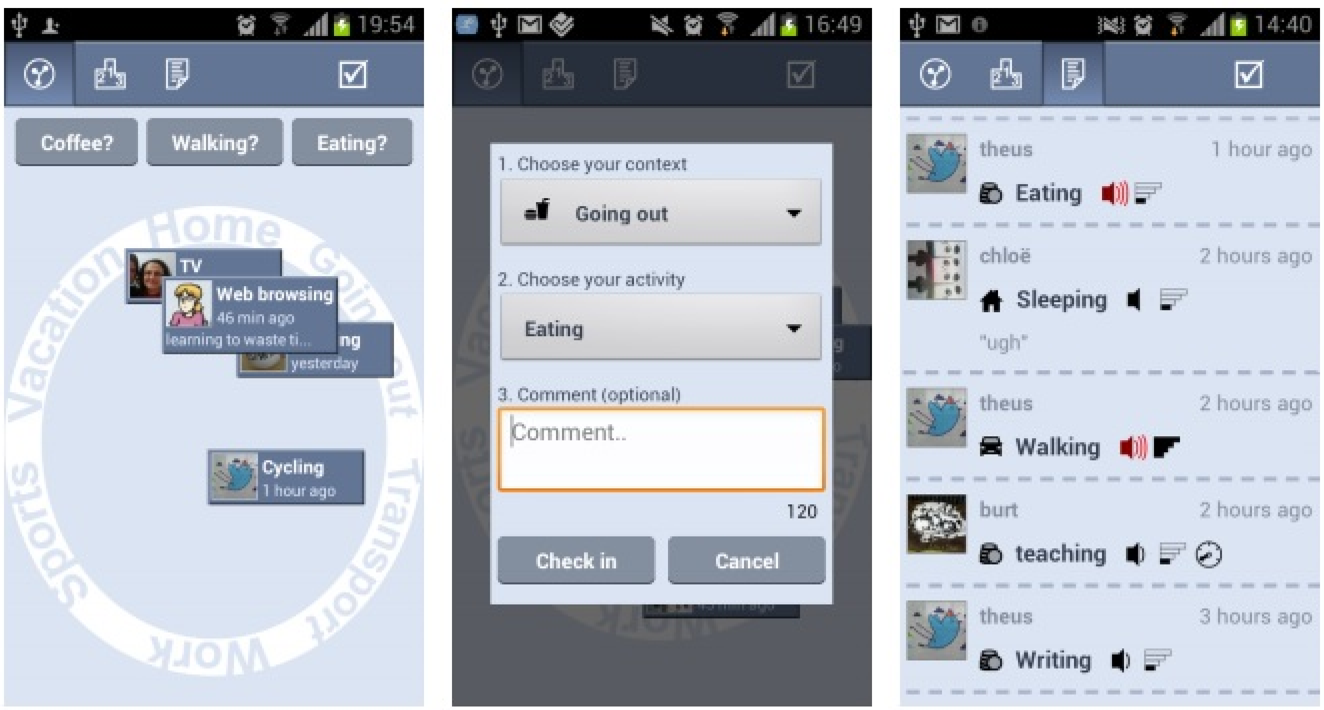


Goals

- Goal 1: Using the phone’s sensor signals, infer the activity the user is about to check-in to.
  - Prediction
  - Suggestion
- Goal 2: To achieve energy efficiency, explore the feasibility of using the phone’s soft sensor signals to infer the activity the user is about to check-in to.
  - Duty-cycling sensors (used by most apps)
  - Soft Sensors VS Physical Sensors
- Goal 3: Identify invalid or fake check-ins using the phone’s physical and software sensor signals.
  - advertising in business model

up2

Up2 is a check-in mobile application was developed by the researchers to achieve their goals



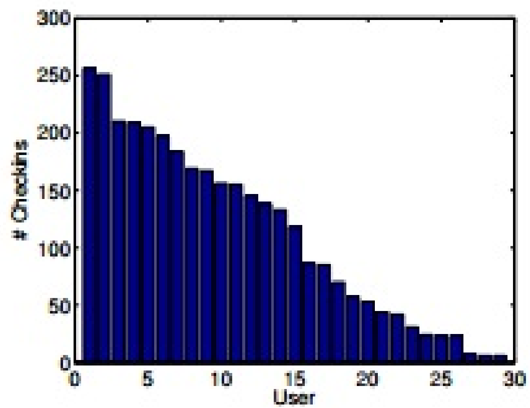
(a) Friends' activities. (b) Check-in screen. (c) Past activities.

Fig. 1: *up2* screen shots.

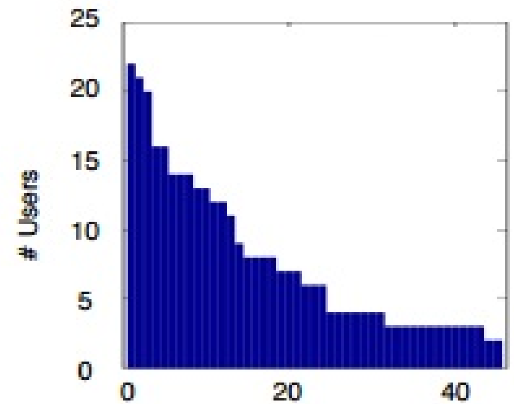
Up2

- suggest 5 check-in activities out of 48 pre-defined activities
- user could define his/her own activity
- each activity belong to one or more context
- 20 users used this application
- over 2700 check-in with 75% from the suggested list
- identified 80% of fake check-ins

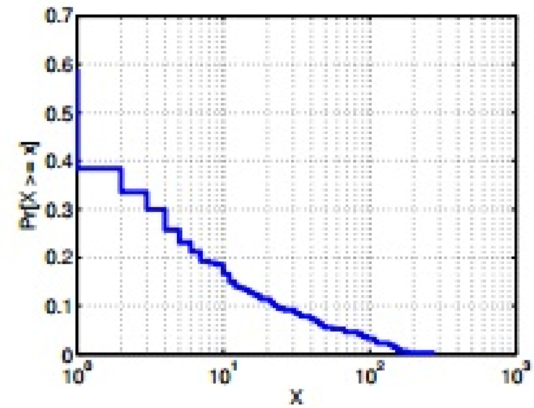
statistics



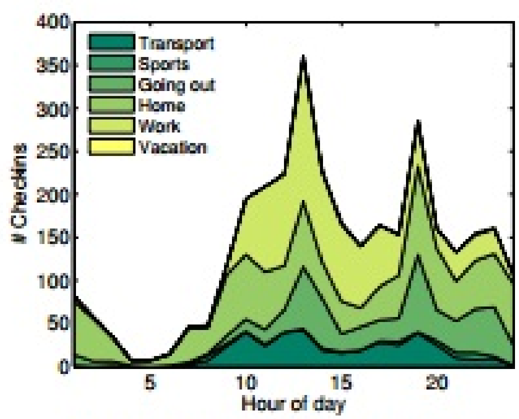
(a) Check-ins per user.



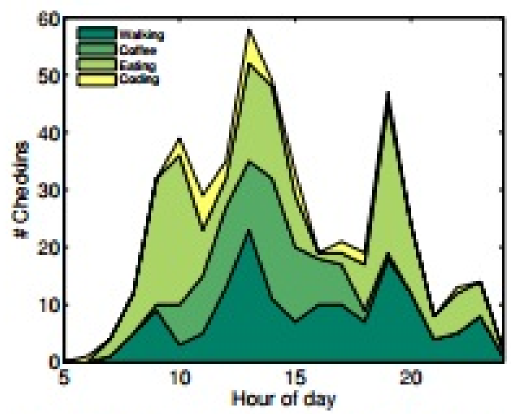
(b) Users per activity.



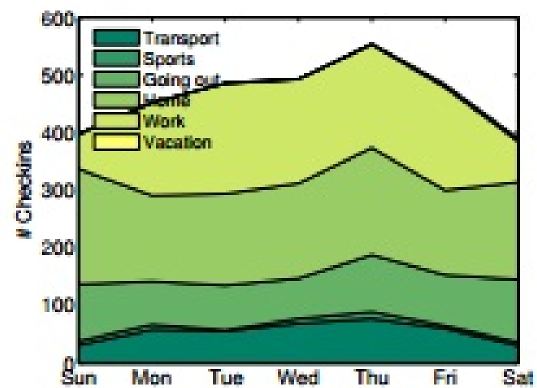
(c) Check-ins per activity.



(d) # check-ins vs. time of day.



(e) Time of day of top activities.



(f) # check-ins vs. day of week.

statistics

- 3200 check-ins from 29 orginal users in 3 European countries
- excluded all users with less than 50 check-ins all the time
- the rest are 2700 check-ins from 20 users
- hour of the day and day of the week
- Daily pattern and weekly pattern

Prediction Features

- Temporal features
- Physical sensors features
- Software sensors features

Temporal features	
F^1 Time of day	$\{0, 1, \dots 23\}$
F^2 Day of week	$\{0, 1, \dots 6\}$
Physical sensor features	
F^3 Acceleration mean	$m_a = \frac{1}{N} \sum_i a_i$
F^4 Acceleration std. dev.	$s_a = \sqrt{\frac{1}{N} \sum_i (a_i - m_a)^2}$
F^5 Noise mean	$m_n = \frac{1}{N} \sum_i n_i$
F^6 Noise std. dev.	$s_n = \sqrt{\frac{1}{N} \sum_i (n_i - m_n)^2}$
F^7 Speed	$\frac{1}{t_N - t_1} \sum_{i=1}^{N-1} d(l_i, l_{i+1})$
F^8 Distance from home	$d(l_N, l_h)$
F^9 Distance from work	$d(l_N, l_w)$
Software sensor features	
F^{10} Previous check-in	{all activity IDs}
F^{11} Battery charging?	Boolean
F^{12} Battery level	$\{1, 2, \dots 100\}$
F^{13} Battery state	{low, medium, high}
F^{14} Network type	{Wi-Fi, cellular, none}
F^{15} Network name	String
F^{16} Last used app category	{app categories}
F^{17} # Proximity events	$\{1, 2, \dots\}$
F^{18} # Screen events	$\{1, 2, \dots\}$
F^{19} # SMS events	$\{1, 2, \dots\}$
F^{20} # Phone calls	$\{1, 2, \dots\}$
F^{21} Recent SMS/Calls?	Boolean
F^* Temporal features	F^1, F^2

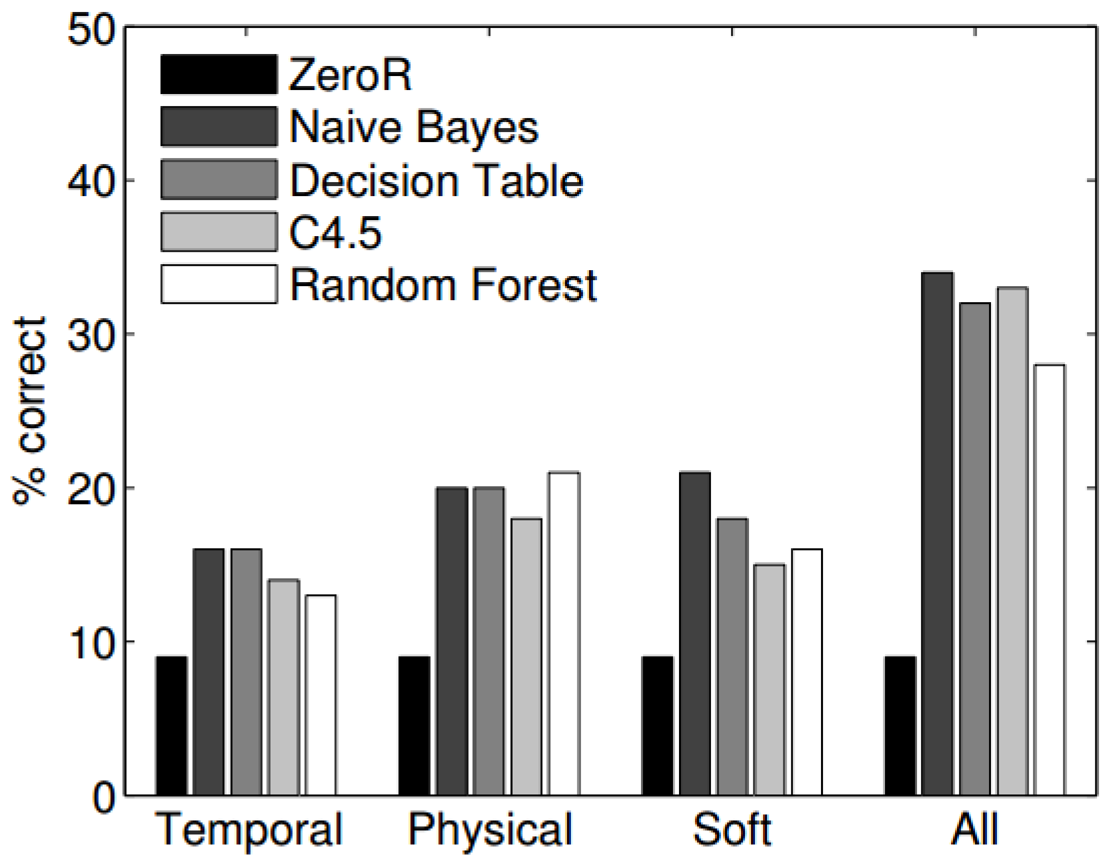
TABLE II: List of prediction features.

Prediction Models

They applied the following machine learning classifiers on each prediction features groups, each group alone, then all groups together to find the most accurate prediction model.

- ZeroR
- Naive Bayes
- Decision Table
- Decision Tree C4.5
- Random Forest

Prediction Models



Choose Naive Bayes model for the rest of evaluation

Check-in Suggestions

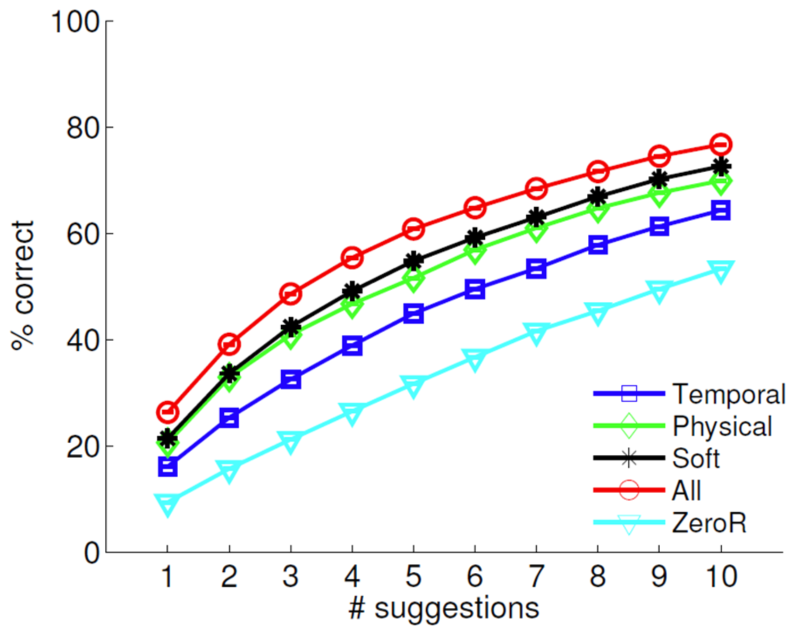


Fig. 4: Prediction accuracy of various feature sets vs. number of suggestions.

Software sensor features achieve an accuracy of 54%, which is close to that of the model with all the features.

Performance steeply increases with the number of suggestions.

After 4 or 5 suggestions, the curve flattens.

CONCLUSION: 4 or 5 suggestions is a good compromise offering high accuracy.

Subject Specific Models

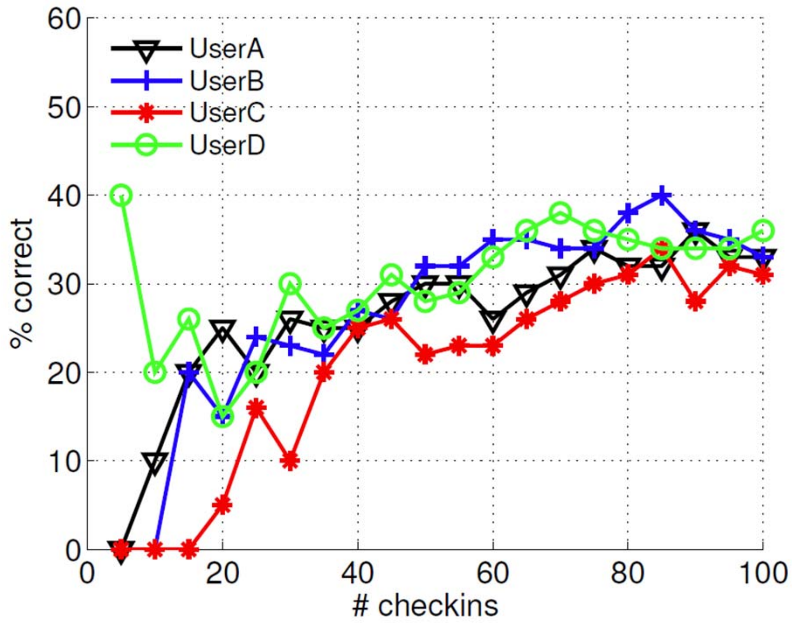


Fig. 5: Prediction accuracy for one suggestion vs # check-ins available for training.

Pick top four users in dataset.

1. 60~70 samples seems sufficient.
2. Accuracy doesn't steadily increase, due to change of user behavior.
3. Individual users are predictable to different degrees.

Subject Specific Models

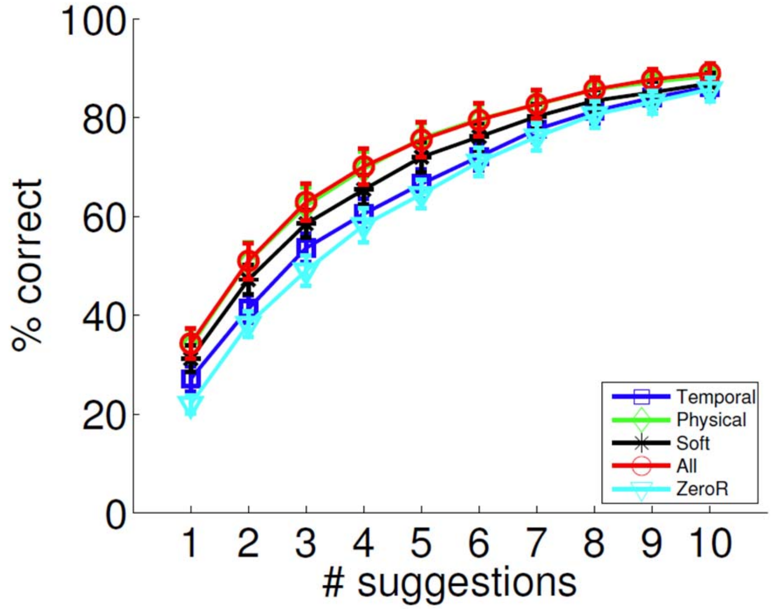


Fig. 6: User specific model: Prediction accuracy vs. # of suggestions.

For 5 recommendations, accuracy of software sensors model is close to the model with all features.

So we consider software sensors over hardware sensors due to energy saving.

Predictability of Activities

Using physical sensors:

Activity	P	R	F
Walking (Transit)	0.82	0.86	0.84
Cycling (Transit)	0.81	0.87	0.84
Drinking (Leisure)	0.78	0.83	0.80
Coffee (Work)	0.71	0.88	0.78
Meeting (Work)	0.69	0.90	0.78

TABLE III: Most predictable activities (physical sensors).

Activity	P	R	F
Eating (Leisure)	0.64	0.71	0.67
Hanging out (Home)	0.71	0.64	0.67

TABLE IV: Least predictable activities (physical sensors).

Using software sensors:

Activity	P	R	F
Coffee (Work)	0.74	0.87	0.80
Coffee (Home)	0.70	0.83	0.76
Meeting (Work)	0.68	0.83	0.75
Drinking (Leisure)	0.70	0.80	0.75
Reading (Home)	0.72	0.76	0.74

TABLE V: Most predictable activities (soft sensors).

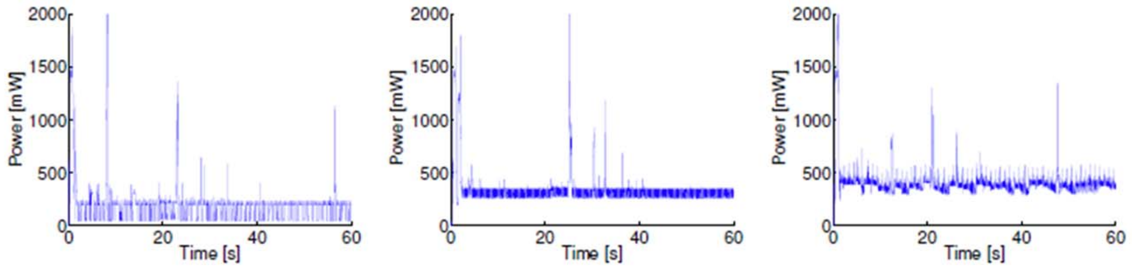
Activity	P	R	F
Cycling (Transit)	0.63	0.73	0.68
Writing (Work)	0.64	0.70	0.67
Walking (Transit)	0.66	0.67	0.67
TV (Home)	0.62	0.71	0.66
Eating (Leisure)	0.64	0.65	0.64

TABLE VI: Least predictable activities (soft sensors).

Physical sensors tend to predict activities with phone movement.

Software sensors tend to predict activities with phone interaction.

Energy Cost of Features



(a) Accelerometer. (b) Microphone. (c) GPS.

Fig. 7: Power consumption of various physical sensors.

Features	Power	Accuracy (# Suggestions, Model type)			
	(mW)	(3, GM)	(5, GM)	(3, USM)	(5, USM)
Soft	~ 0	42%	54%	58%	72%
Physical	561	40%	51%	62%	75%
All	~ 561	48%	60%	62%	75%

TABLE VII: Power consumption vs. prediction accuracy of features (GM: Generic Model; USM: User Specific Model).

Of physical sensors, accelerometer costs least and GPS costs most.

Energy cost of software sensors is negligible.

No big difference between software and physical sensors.

VERIFICATION

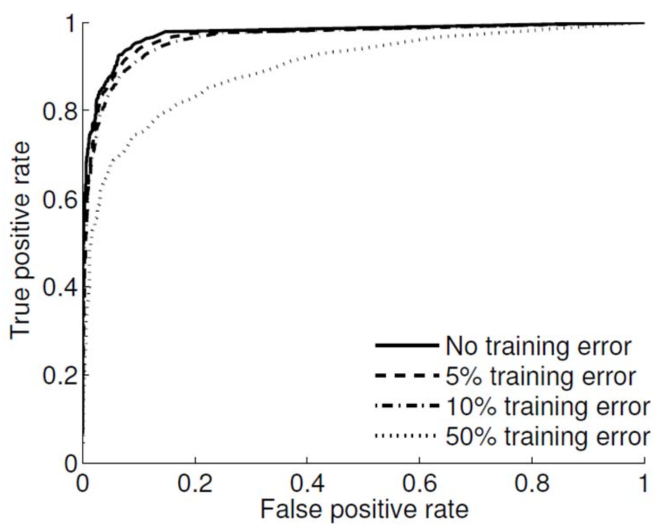


Fig. 8: ROC curve for verification performance.

We can successfully filter fake check-ins even if we have significant amounts of fake training data.

CONCLUSION

- Use sensors to support check-ins.
- Provide suggestions to speed up check-ins.
- Found 5 suggestions for check-ins are appropriate.
- Verify check-ins and prevent erroneous check-ins.
- Show soft sensors are viable option for predicting check-ins.

References

- http://fmlight.com/facebook-check-in-what-to-know/

Questions?