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# Indoor Positioning with WiFi Signals

## Device Self-Calibration using Histograms

Christos Laoudias<sup>\*</sup>, Robert Piché<sup>†</sup> and Christos Panayiotou<sup>\*</sup>

<sup>\*</sup>KIOS Research Center for Intelligent Systems and Networks, University of Cyprus

<sup>†</sup>Tampere University of Technology, Tampere, Finland

# Inside or Outside?

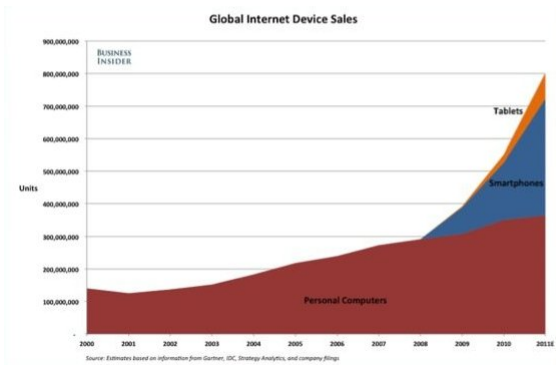
Time spent ...



People spend 80-90% of their time indoors  
70% of cellular calls and 80% of data connections originate from indoors.

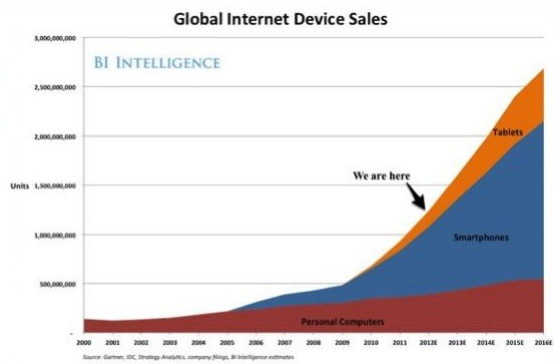
*(Source Strategy Analytics)*

# Smartphone Facts



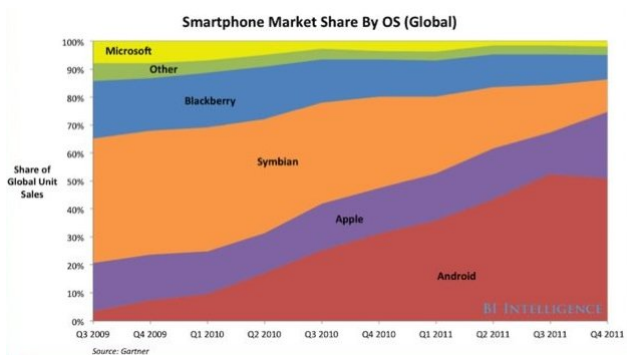
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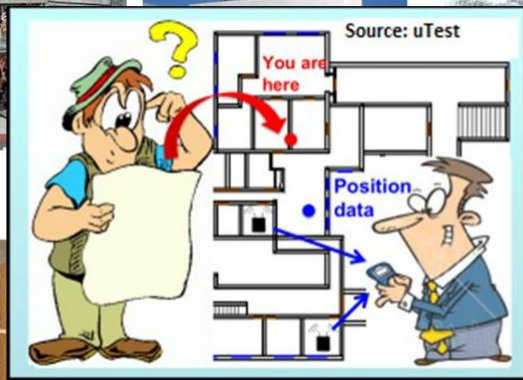
- ▶ In 2011 the smartphone sales outnumbered the PC sales for the first time
- ▶ Predictions suggest that smartphones will dominate the computing device market
- ▶ The Android is now (and will probably remain) the leading OS

# Target Indoor Environments



Source: google images

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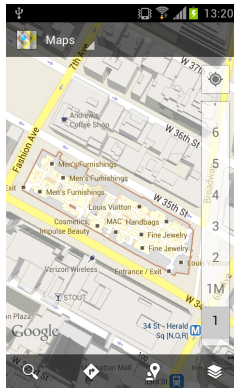
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# Google Maps Mobile Goes Indoor

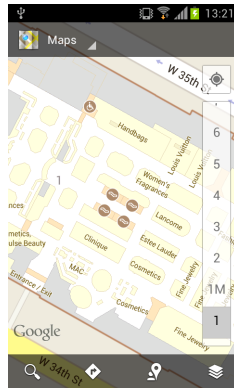
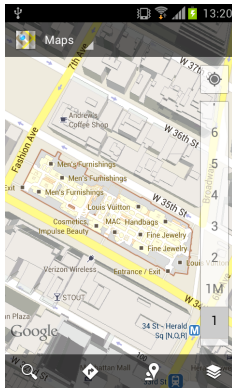




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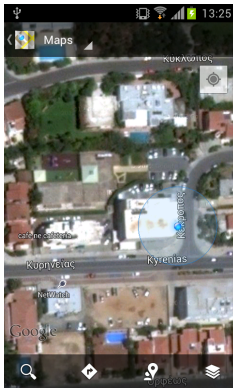


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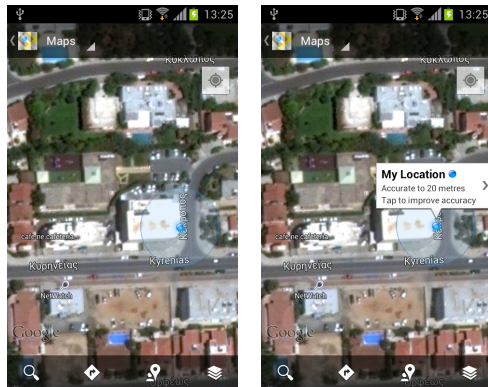


- ▶ Launched in 2011 with 60 venues in the U.S. and 50 in Japan
- ▶ Now has ~10,000 maps and offers indoor walking directions
- ▶ Indoor geo-location based on WiFi signal triangulation (rumoured)

# What about accuracy?

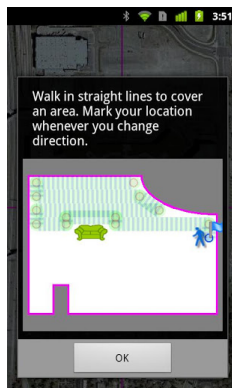
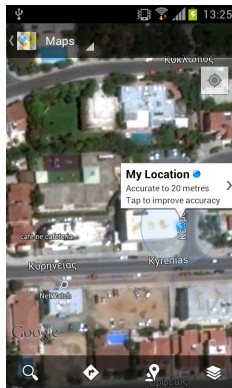
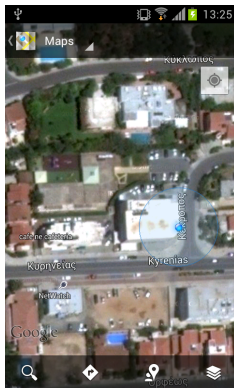


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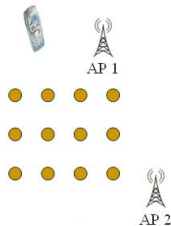
- ▶ The accuracy is around 20–50m (depending on the AP density)
- ▶ Google Floor Plan Marker app promises to improve accuracy (floorplan map is required)

# Signal Strength Fingerprints



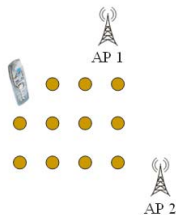
Where am I?

# Fingerprint-based Positioning



- ▶ **Offline phase:** Build RSS radiomap with a reference device  $D_0$ 
  - ▶  $n$  APs deployed
  - ▶ Fingerprints
$$r_i = [r_{i1}, \dots, r_{in}]^T$$
  - ▶ Averaging
$$\bar{r}_i = \frac{1}{M} \sum_{m=1}^M r_i(m)$$
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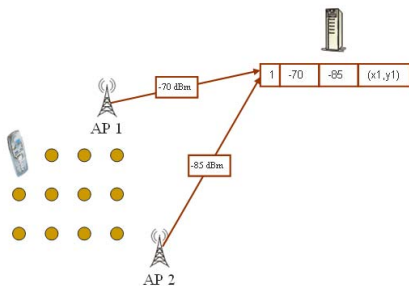
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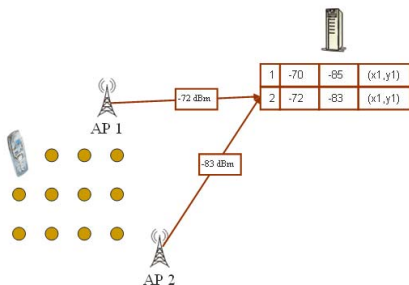


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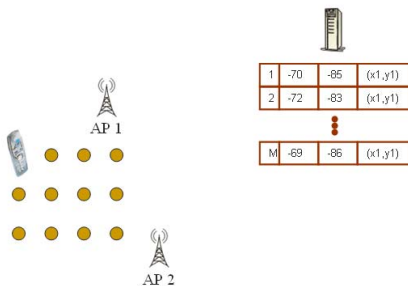
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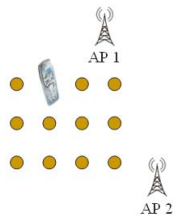
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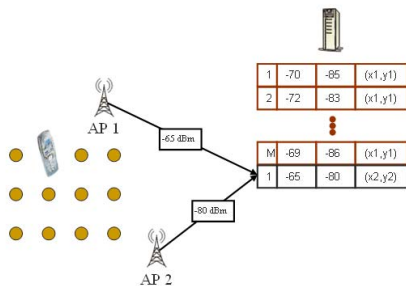
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1	-70	-85	$(x_1, y_1)$
2	-72	-83	$(x_1, y_1)$
⋮			
M	-69	-86	$(x_1, y_1)$

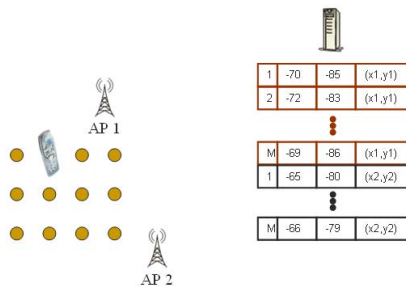
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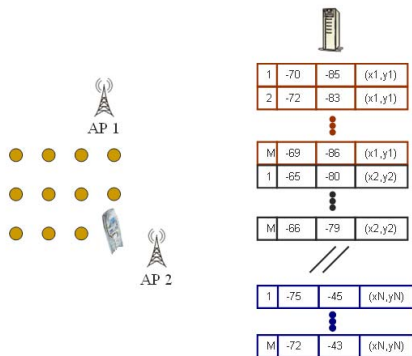
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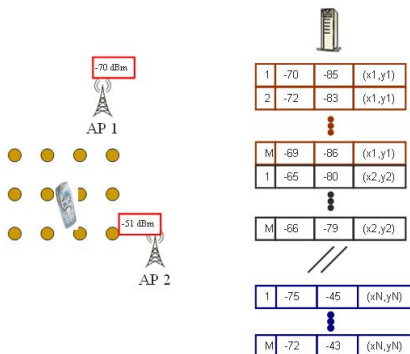
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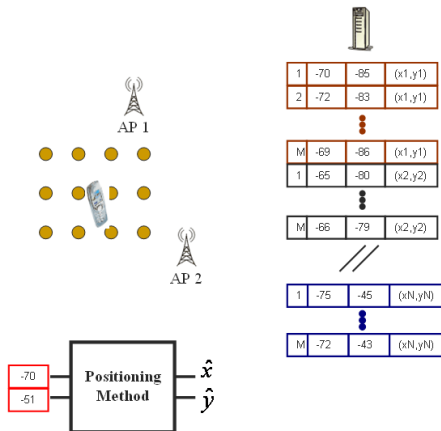
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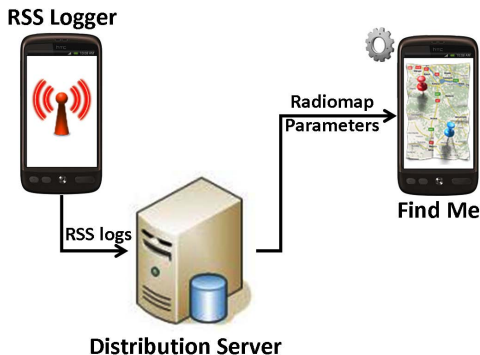
► Calculate  $\hat{\ell}$  using the radiomap

# Airplace: Indoor Positioning on Android Devices

## Terminal-based Infrastructure-assisted Architecture

- ▶ **Low Communication Overhead:** Avoids uploading the observed RSS fingerprint to the positioning server
- ▶ **User Privacy & Security:** Location is estimated by the user

<http://www2.ucy.ac.cy/~laoudias/pages/platform.html>



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  - ▶ The WiFi standard (IEEE 802.11) defines the RSS Indicator (1 byte integer) for measuring RSS in  $[0 \ 255]$
  - ▶ The implementation of each vendor is limited in  $[0 \ \text{RSSI}_{\text{max}}]$
  - ▶ RSSI is mapped to actual power values in dBm internally by the device driver (proprietary information)
  - ▶ Even worse: same chipsets may not report the same RSS values due to different antennas or packaging material

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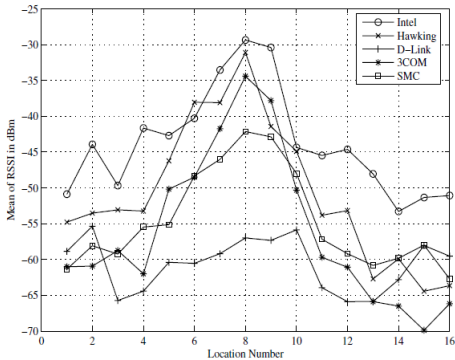
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  - ▶ Even worse: same chipsets may not report the same RSS values due to different antennas or packaging material
- ▶ Using a new device for positioning is feasible, but the RSS values are not compatible with the radiomap, leading to accuracy degradation
- ▶ Best accuracy is guaranteed only if the the user carries the same device during positioning, otherwise a *calibration* step is required

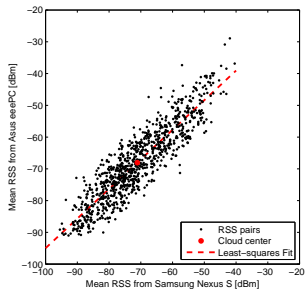
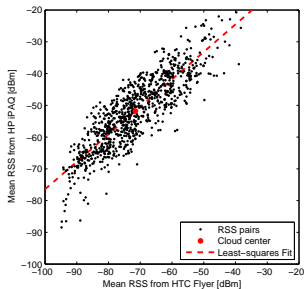
# Device Diversity

Vendor	Model	Chipset	Max (dBm)	Min (dBm)	Range
3COM	3CRUSB10075	unknown	+10	-94	104
D-Link	AirPlus DWL-650+	Texas Instrument	-50	-100	50
SMC	EZ Connect SMC2635W	ADMTek	-14	-82	68
Hawking Technology	HWC54G Rev.R	Prism GT	0	-75	75
Intel	PRO/Wireless 2200BG	Intel	-10	-84	74



Source: K. Kaemarungsi (2006)

# Good News: Linear relation between RSS values

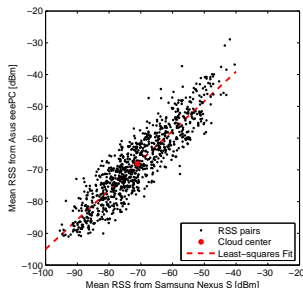
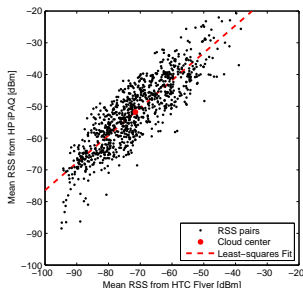


- **Manual Calibration:** Collect several colocated RSS pairs at *known* locations and estimate the linear coefficients through least squares

$$\bar{r}_{ij}^{(2)} = \alpha_{12}\bar{r}_{ij}^{(1)} + \beta_{12}$$



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- ▶ **Manual Calibration:** Collect several colocated RSS pairs at *known* locations and estimate the linear coefficients through least squares

$$\bar{r}_{ij}^{(2)} = \alpha_{12}\bar{r}_{ij}^{(1)} + \beta_{12}$$

- ▶ **Limited Applicability:** (i) User needs to be familiar with the indoor area and (ii) a considerable data collection effort is required

# Can we do it more efficiently?

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## Objectives

- ▶ Fully automatic approach with short calibration time
- ▶ Runs concurrently with positioning while the user walks around
- ▶ No user intervention or tedious data collection

## Idea

- ▶ Perform device self-calibration on-the-fly using histograms of RSS values observed simultaneously with positioning

# RSS Histograms

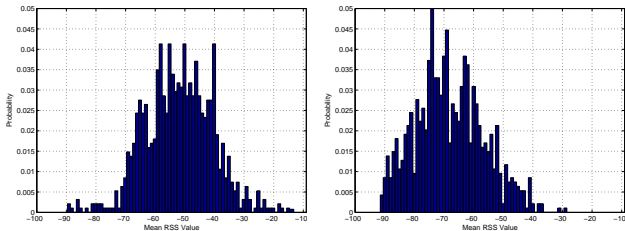


Figure: HP iPAQ (left) and Asus eeePC (right)

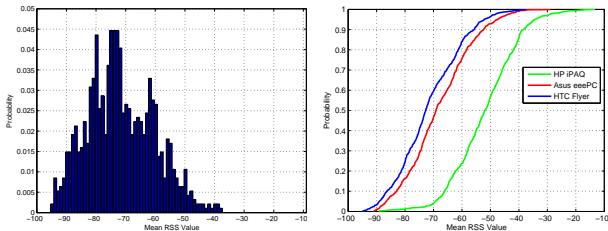
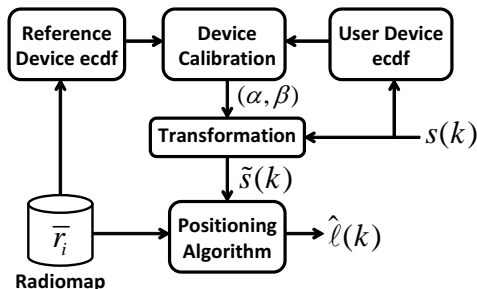


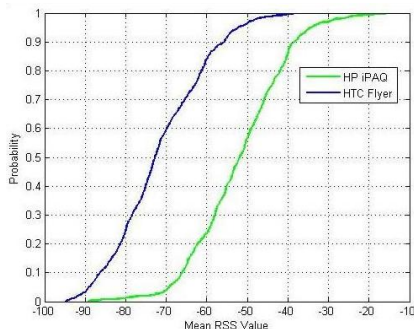
Figure: HTC Flyer (left) and Empirical cdfs (right)

# Self-Calibration Method



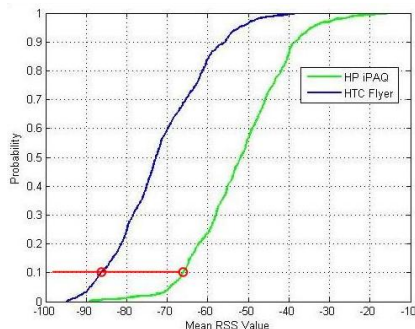
1. Create the RSS ecdf of the reference device by using the radiomap
2. Create and update the ecdf of the new device by using  $s(k)$
3. Fit a linear mapping between the reference and new device to obtain the parameters  $(\alpha, \beta)$  by using “representative” ecdf values
4. Transform the observed RSS values with  $\tilde{s}_j(k) = \alpha s_j(k) + \beta$
5. Estimate location  $\hat{\ell}(k)$  with any fingerprint-based algorithm

# Inverse ecdf Linear fitting



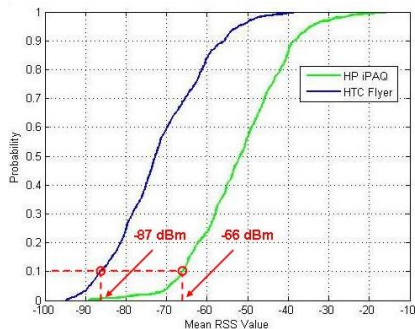
- ▶  $F(x)$  gives the probability that the RSS value is less than  $x$ ,  $F^{-1}(y)$  returns the RSS value that corresponds to the  $y$ -th cdf percentile
- ▶  $F_r(x)$  and  $F_u(x)$  denote the ecdf of the reference and user device
- ▶ Obtain  $(\alpha, \beta)$  from  $F_r^{-1}(y) = \alpha F_u^{-1}(y) + \beta$ ,  $y \in \{0.1, 0.2, \dots, 0.9\}$
- ▶  $(\alpha, \beta)$  are initialized to  $(1, 0)$  and updated periodically (e.g. every 10 sec) thereafter, while the user is walking

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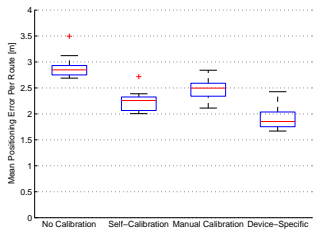
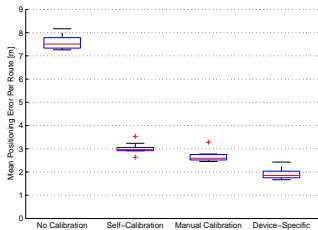


Figure: HTC Flyer user with HP iPAQ (left) or Asus eeePC (right) radiomap



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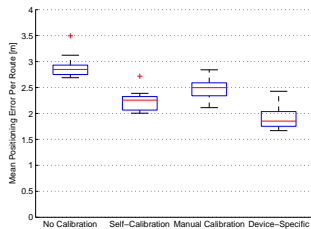
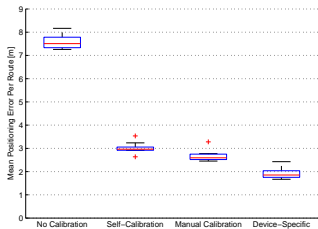
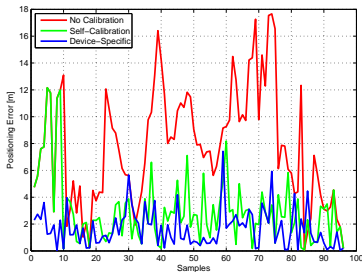


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# Results with 5 devices

**Table:** Median of the mean error  $\bar{\epsilon}$  [m], with and without calibration.

	<b>iPAQ</b>	<b>eeePC</b>	<b>Flyer</b>	<b>Desire</b>	<b>Nexus S</b>
<b>iPAQ</b>	2.7	2.8 (6.6)	3.0 (7.5)	2.9 (8.4)	2.6 (7.7)
<b>eeePC</b>	2.8 (4.4)	2.3	2.3 (2.8)	2.6 (3.5)	2.5 (2.9)
<b>Flyer</b>	3.2 (5.9)	2.6 (3.0)	1.9	2.1 (2.3)	2.6 (2.7)
<b>Desire</b>	3.4 (6.1)	2.8 (3.2)	2.5 (2.5)	2.4	2.5 (2.6)
<b>Nexus S</b>	3.0 (6.2)	2.6 (2.8)	2.7 (2.7)	2.4 (2.5)	2.3

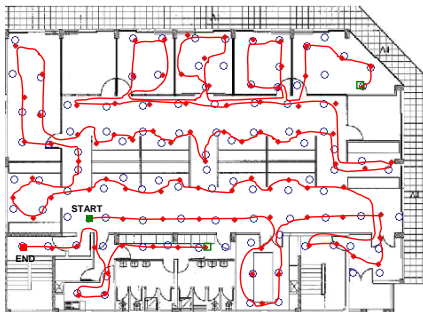
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Thank you for your attention  
Questions?

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# Extra Slides

# Experimental Setup @ KIOS



- ▶ 560 m<sup>2</sup> office, 9 WiFi APs, 5 devices (1 HP iPAQ PDA, 1 Asus eeePC laptop, 1 HTC Flyer Android tablet, 2 Android smartphones)
- ▶ **Training Data:** 105 reference locations, 20 fingerprints per location (2100 in total) with each device for comparison
- ▶ **Testing Data:** Route with 2 segments, 96 test locations, 1 fingerprint per location, route sampled 10 times

# Inverse ecdf Least Squares Fitting

If  $\mathbf{u}$  is a continuous random variable and  $\mathbf{y} = f(\mathbf{u})$  with monotonically increasing  $f$  then  $f = F_{\mathbf{y}}^{-1} \circ F_{\mathbf{u}}$ . In particular, the inverse cdf ordered pairs

$$\{(u_i, y_i) = (F_{\mathbf{u}}^{-1}(q_i), F_{\mathbf{y}}^{-1}(q_i)) : q_i \in \{0.1, \dots, 0.9\}\}$$

lie on the curve  $y = f(u)$ .

## Proof:

We have

$$\begin{aligned} F_{\mathbf{u}}(u) &= P(\mathbf{u} \leq u) = P(f(\mathbf{u}) \leq f(u)) = \\ &= P(\mathbf{y} \leq f(u)) = F_{\mathbf{y}}(f(u)). \end{aligned}$$

Applying  $F_{\mathbf{y}}^{-1}$  to both sides gives the identity  $f = F_{\mathbf{y}}^{-1} \circ F_{\mathbf{u}}$ . Also, the components of the inverse cdf ordered pairs satisfy

$$y_i = F_{\mathbf{y}}^{-1}(q_i) = F_{\mathbf{y}}^{-1}(F_{\mathbf{u}}(u_i)) = f(u_i).$$