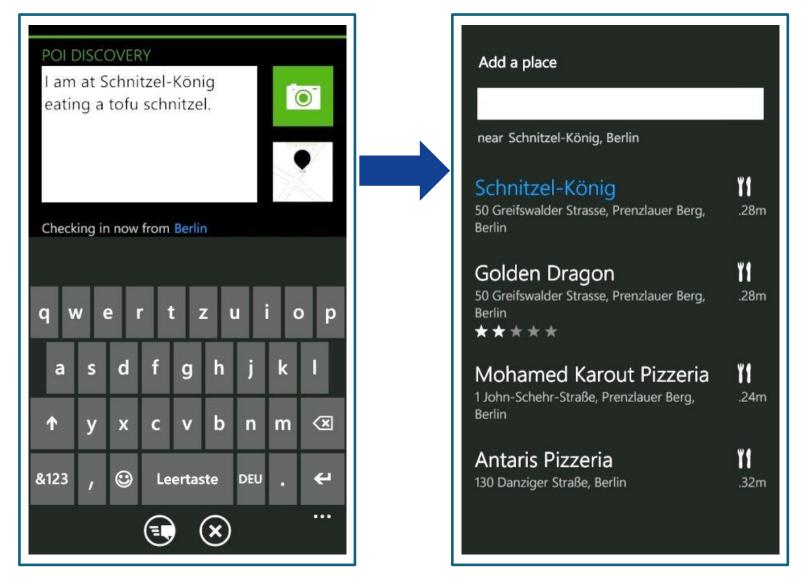
Relevance Optimization of Check-In Candidates

Steffen Bickel

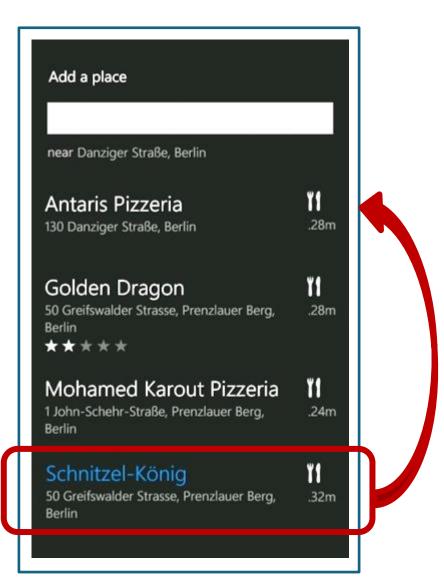


Check-In from Nokia Pulse App



NOKIA

Goal: Show Check-In Place at Rank 1



Goal: Show Check-In Place at Rank 1

Main Performance Measure: Precision@1

Precision@1 is percentage of cases where correct check-in place is shown at rank 1 of the candidate list.

Goal: Show Check-In Place at Rank 1 or Within Top-5 Results

Also important for a good user experience:



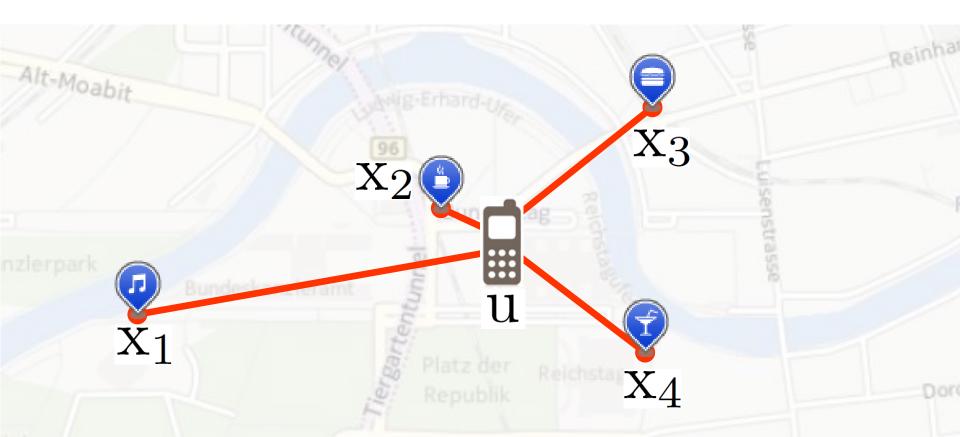
Precision@5 is percentage of cases where correct check-in place is shown within top-5 results of candidate list.

Relevance Modeling

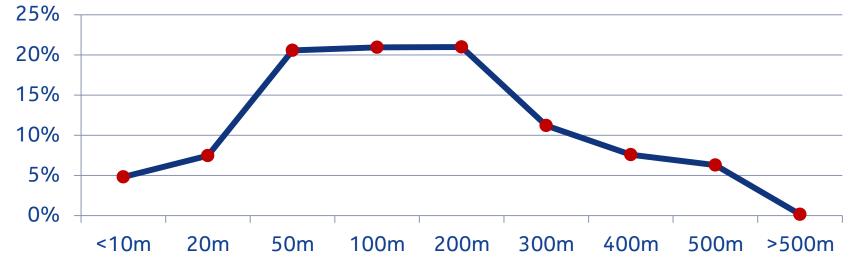


Relevance Factor: Distance = Baseline

score(x, u) = -dist(x, u)



Inaccuracy of Geo-Positions



Geo-Distance between GPS Position and Position of Check-in Place





Places with many historic check-ins are more relevant

Closer places are more relevant

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$score(x, u) = (\alpha + n_x) e^{-dist(x, u)/\sigma}$

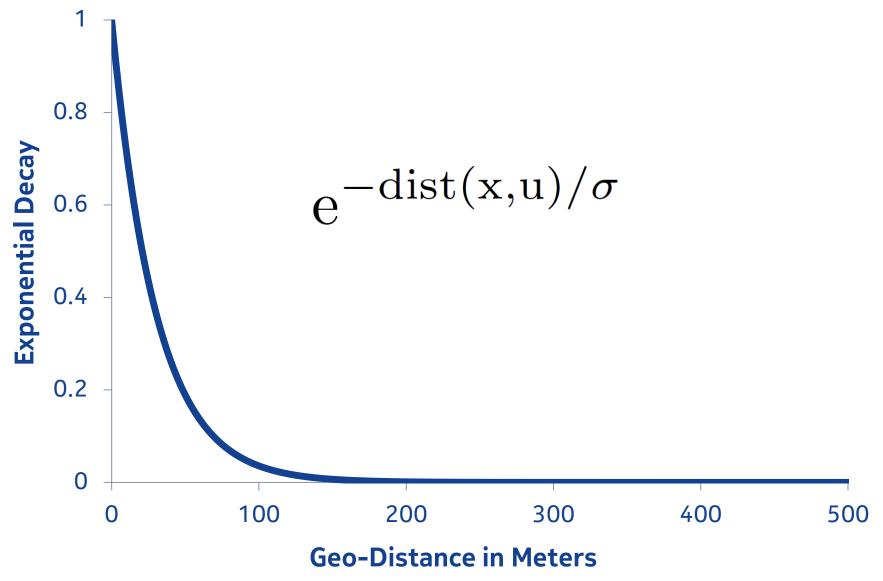
constant base count number of historic checkins on place x

exponential decay on geo-distance to x

Places with many historic check-ins are more relevant

Closer places are more relevant

Exponential Decay on Geo-Distance



NOKIA

$score(x, u) = (\alpha + n_x) e^{-dist(x, u)/\sigma}$

constant base count number of historic checkins on place x

exponential decay on geo-distance to x

Places with many historic check-ins are more relevant

Closer places are more relevant

Personalization





Personalization

$$score(x, u) = (\alpha + n_x + \beta n_{xu}) e^{-dist(x, u)/\sigma}$$

number of historic check-ins (all users)

number of personal historic check-ins

exponential decay on geo-distance to x

Places with many historic check-ins are more relevant Revisits by current user are more relevant

Closer places are more relevant

Bootstrapping with Search Clicks

 $\operatorname{score}(\mathbf{x}, \mathbf{u}) = (\alpha + n_{\mathbf{x}} + \beta n_{\mathbf{x}\mathbf{u}} + \gamma c_{\mathbf{x}}) e^{-\operatorname{dist}(\mathbf{x}, \mathbf{u})/\sigma}$

number of historic check-ins (all users)	number of personal historic check- ins	number of clicks on place x in search results	exponential decay on geo- distance to x
Places with many	Revisits by	Searched	Closer places
historic check-ins	current user are	places are	are more
are more relevant	more relevant	more relevant	relevant

Parameter Learning and Evaluation Setup

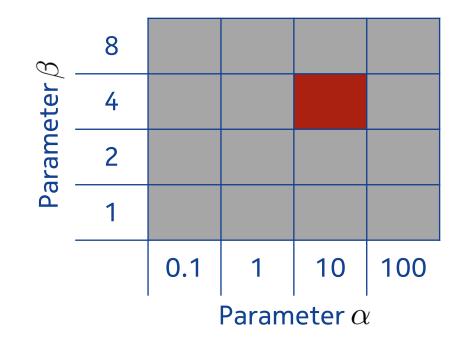


4 Parameters Need to be Learned

$score(x, u) = (\alpha + n_x + \beta n_{xu} + \gamma c_x) e^{-dist(x, u)/\sigma}$

Parameter Learning with Grid Search – Machine Learning for Slackers

All parameter combinations in grid are evaluated on tuning data. Combination with best Precision@1 is chosen.



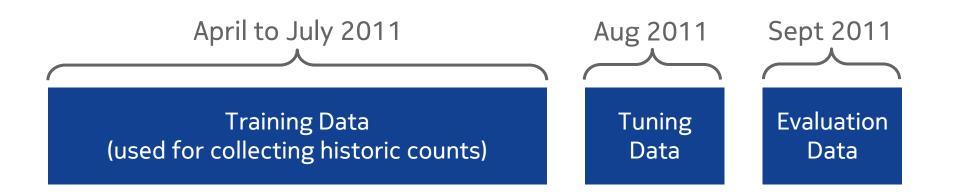
4 Parameters Need to be Learned

$$score(x, u) = (\alpha + n_x + \beta n_{xu} + \gamma c_x) e^{-dist(x, u)/\sigma}$$

4 parameters \rightarrow 4 dimensional search grid

Evaluation Setup

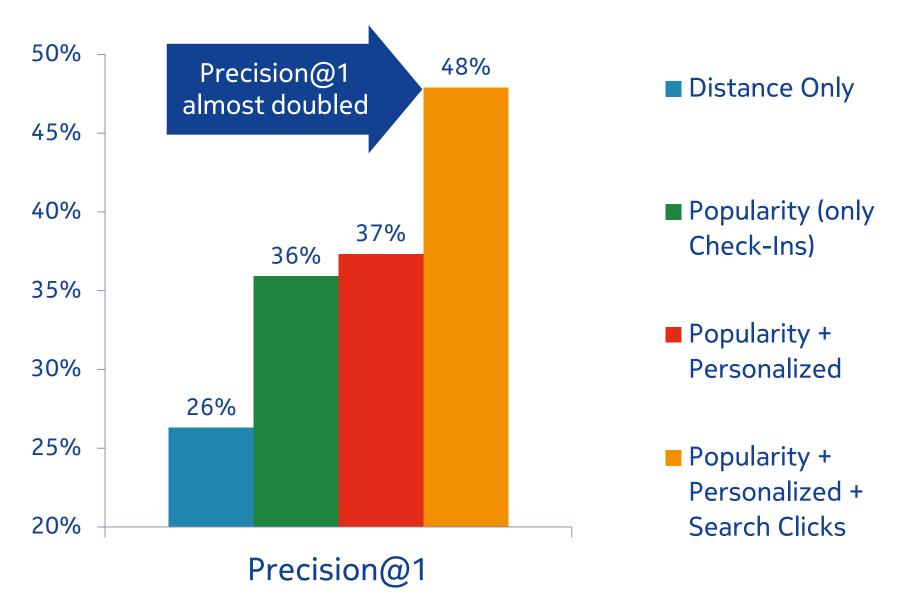
Split of historic check-in data into 3 chunks.



Evaluation Results

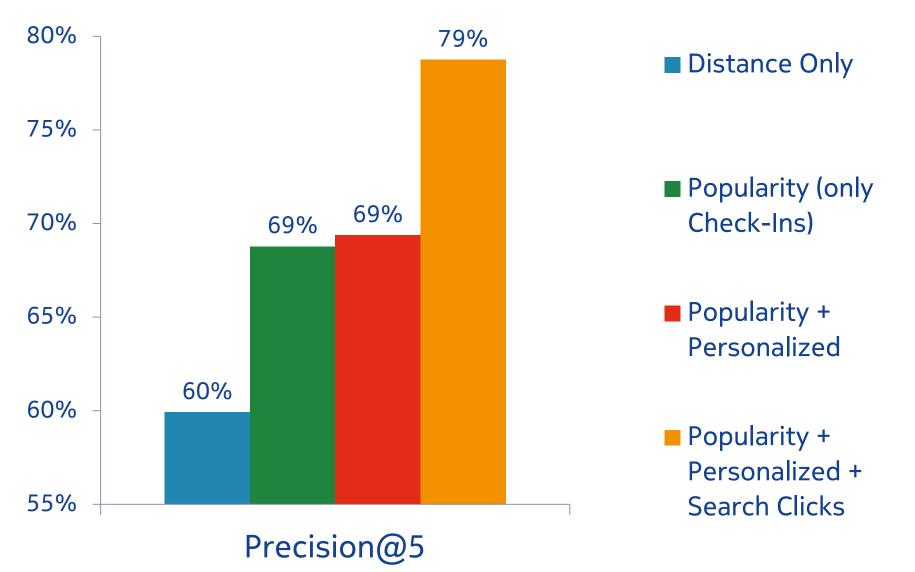


Evaluation of Relevance Model



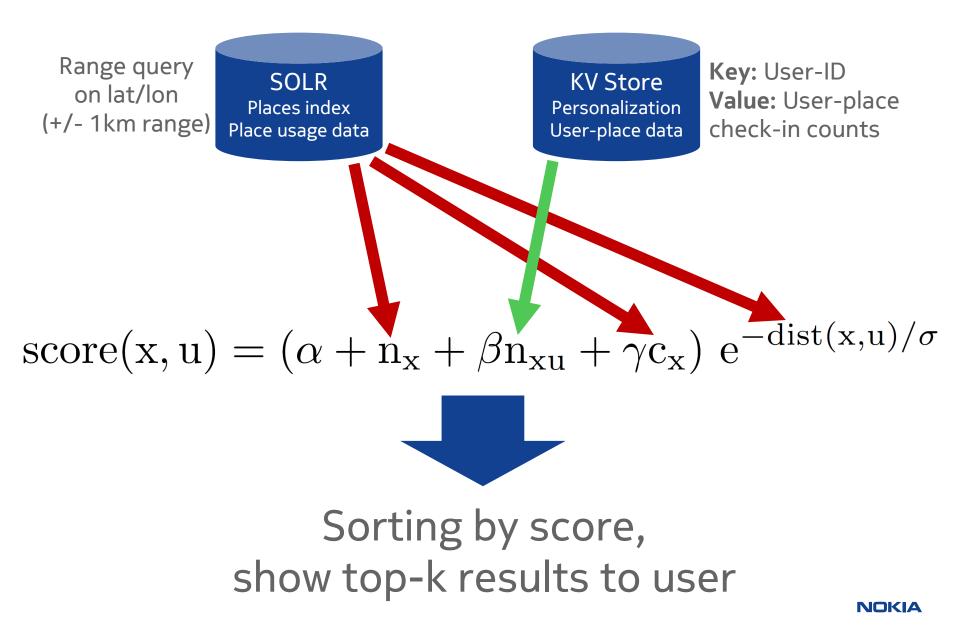
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Evaluation of Relevance Model (Prec@5)



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Implementation in Production: Sketch



Summary

- Relevance model improves Precision@1 from 26% to 48%
- Usage data from different use-case (search clicks) helps.
- Grid search on model parameters is very simple but powerful way of doing machine learning.
- Statistical relevance model easy to implement in production on top of SOLR.



Thank You!

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