



Resource-Aware On-Line RFID Localization Using Proximity Data

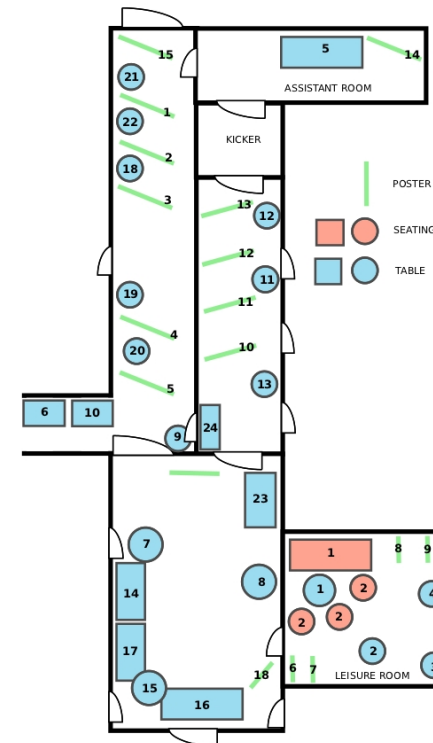
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Germany*



1. Application Context
2. Method
 - Benchmark
 - Social Boosting
3. Dataset
4. Results
5. Summary





1. Application Context

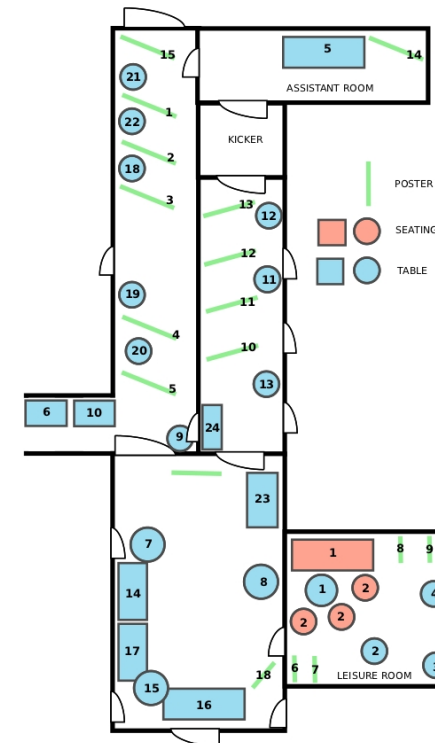
2. Method

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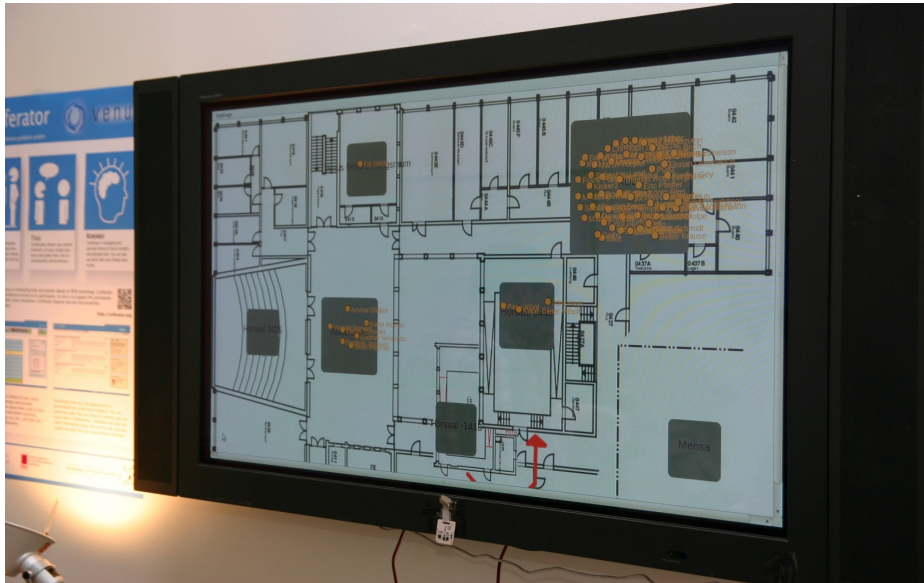
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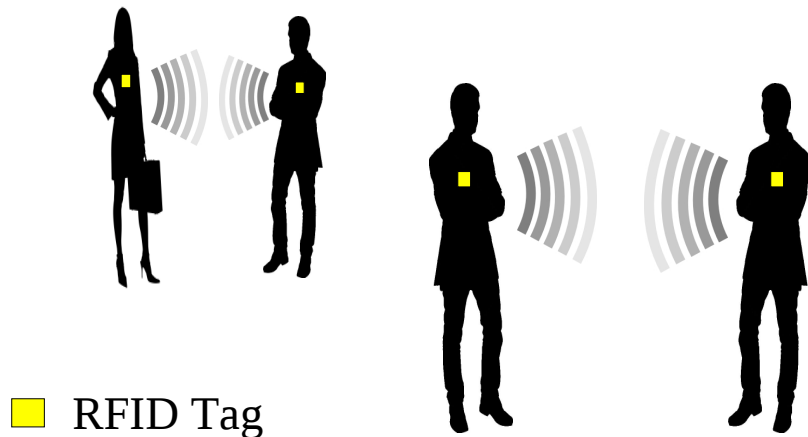
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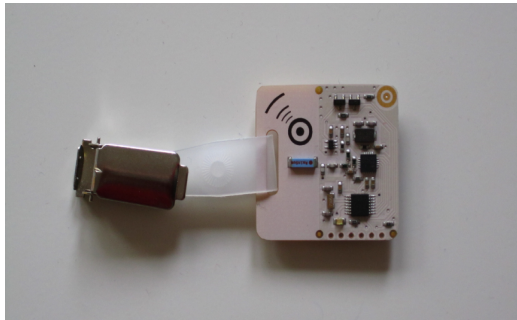
Localization of Conferences



- development of a social network for conferences (www.conferator.org)
- offers contact history for participants
- analysis of contact data
- indoor-localization (room level)



■ RFID Tag



provided by
SocioPatterns

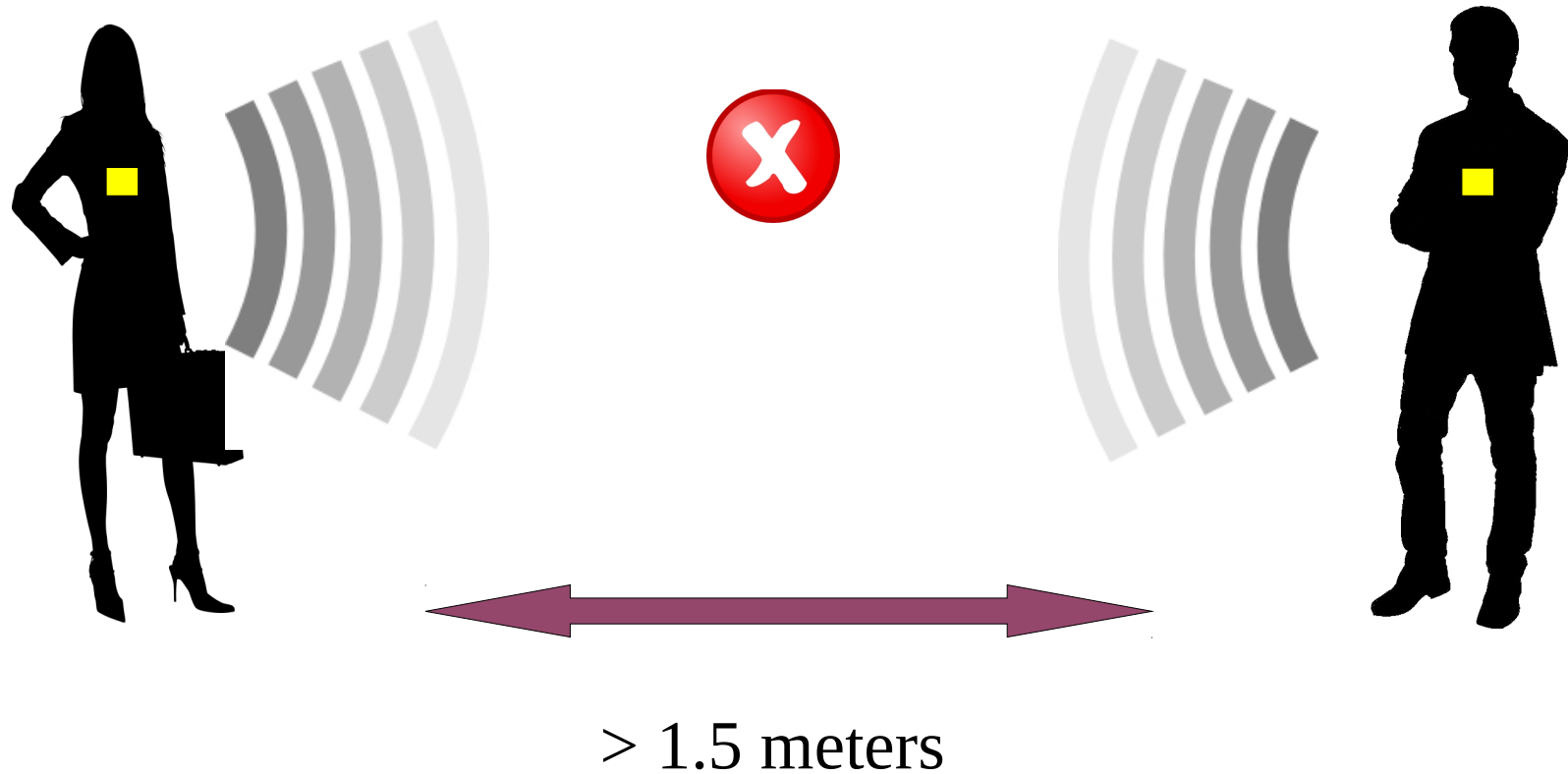
- active RFID tag
- detects other proximity tags within a range of up to 1.5 meters
- done by sending out special proximity packages
- sends one tracking package in four different signal strengths every two seconds
- cannot store information



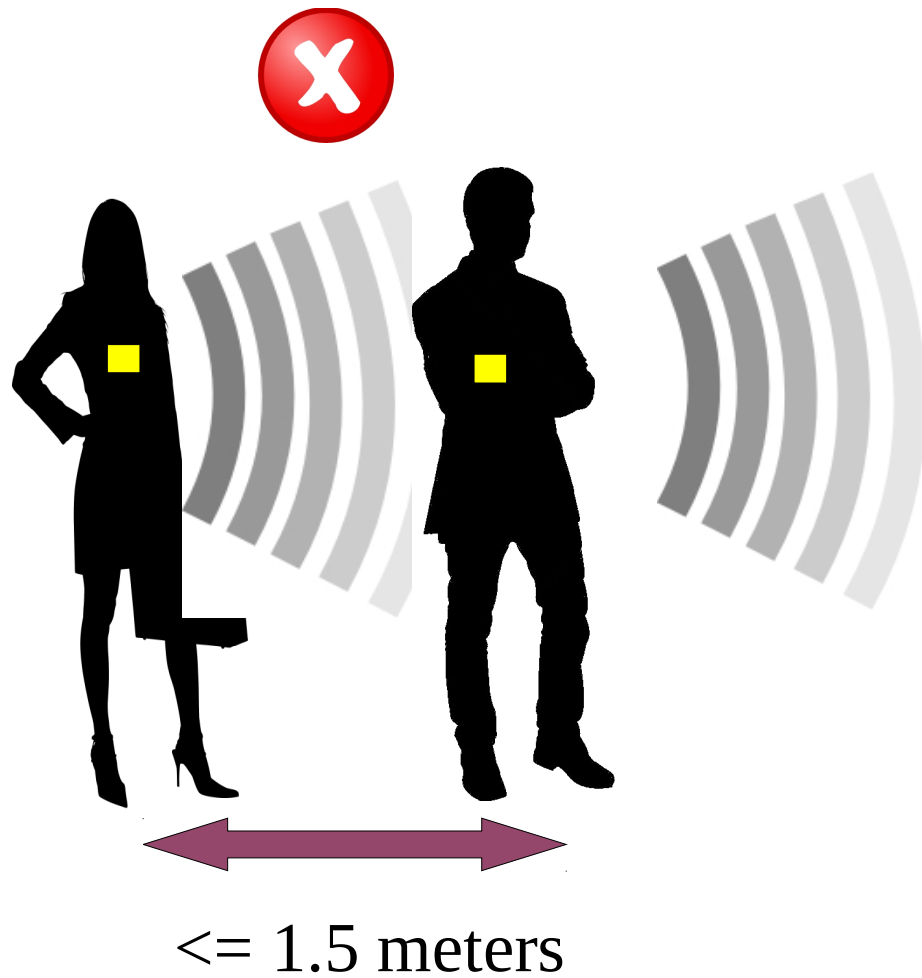
provided by
bit *manufaktur*

- receives RFID signals from proximity tags and forwards them to a central server
- does not provide information like Angle of Arrival (AoA) or Received Signal Strength (RSS)

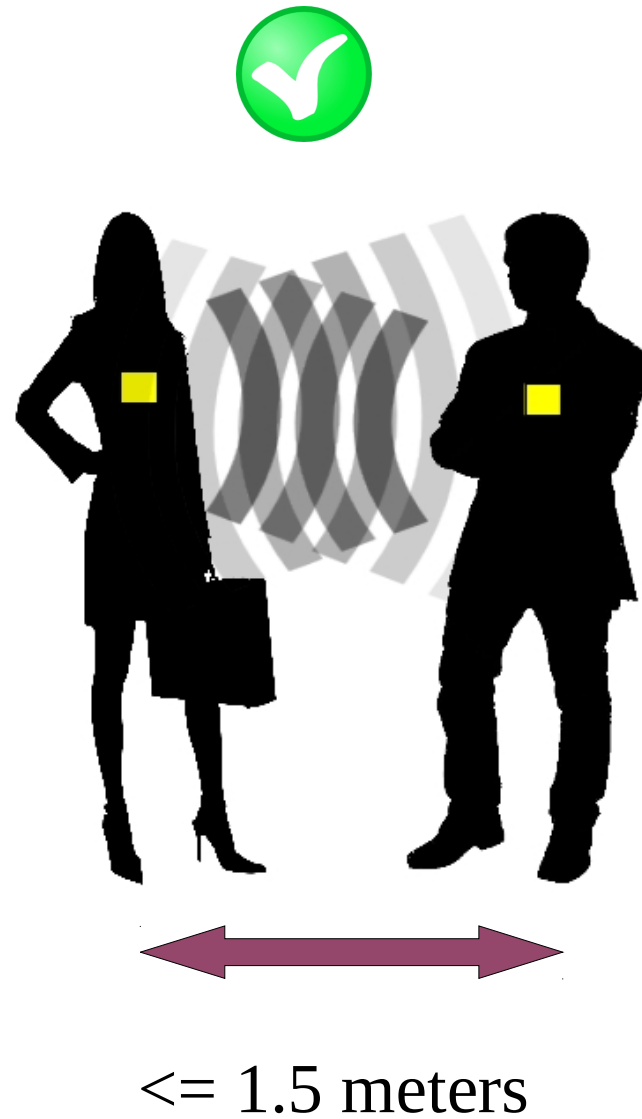
Contact Recognition



Contact Recognition



Contact Recognition

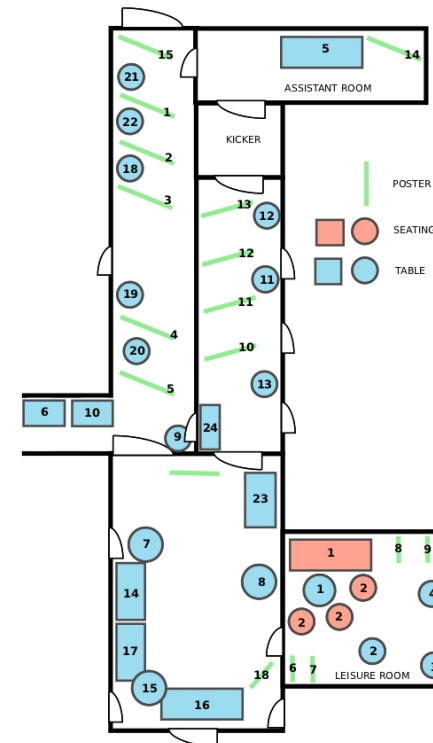




- first explicit analysis that contact information helps to improve localization accuracy
- use of real-time data
- evaluation of state-of-the-art machine learning techniques for room-level localization
- resource-aware application
 - use of limited number of readers
 - use of cost-effective technology



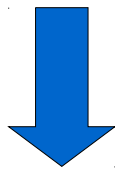
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Assumption

The number of packages an RFID reader receives is significantly dependent on the position of the sending RFID tag.



We determine a set of characteristic vectors for each room in the conference area.

Characteristic Vector



3 tracking packages were received by reader 1 from proximity tag 1135 with signal strength 4 within the last 10 seconds.



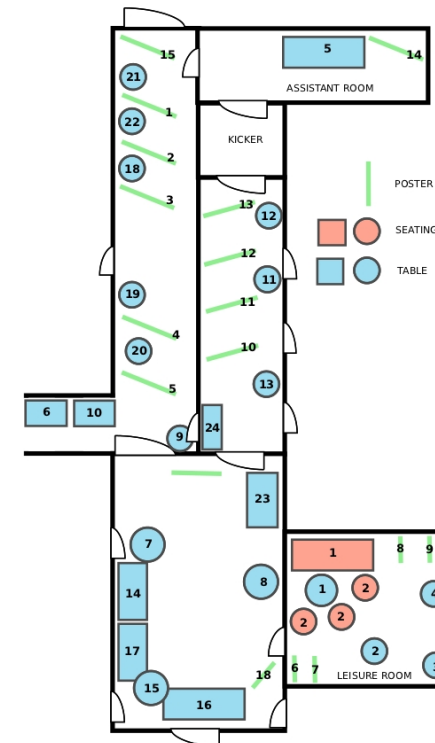
Benchmark

four state of the art machine learning methods:

- Naive Bayes (NBAY)
- K-Nearest Neighbor (KNN)
- Support Vector Machines (SVM) (radial kernel)
- Random Forest (RF)



1. Application Context
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Mean-Approach



Goal: Prediction of user u 's position at time t ,
given time window l

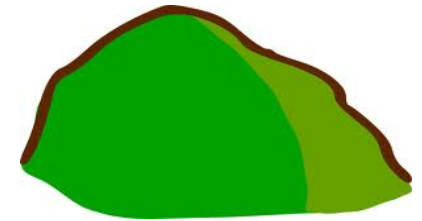
1. determine all contacts $C(u)$ of user u at time t
2. set

$$charVec_{mean}(u, l) = \frac{charVec(u, l) + \sum_{i \in C(u)} charVec(i, l)}{1 + |C(u)|}$$

3. use $charVec_{mean}(u, l)$ as input vector for the prediction algorithm



Max-Approach



Goal: Prediction of user u 's position at time t ,
given time window l

1. determine all contacts $C(u)$ of user u at time t
2. set

$$\mathit{charVec}_{\max}(u, l) = \left(\max_{i \in C(u) \cup \{u\}} \{ \mathit{charVec}(u, l)_1 \}, \dots, \max_{i \in C(u) \cup \{u\}} \{ \mathit{charVec}(u, l)_{4r} \} \right)$$

3. use $\mathit{charVec}_{\max}(u, l)$ as input vector for the prediction algorithm



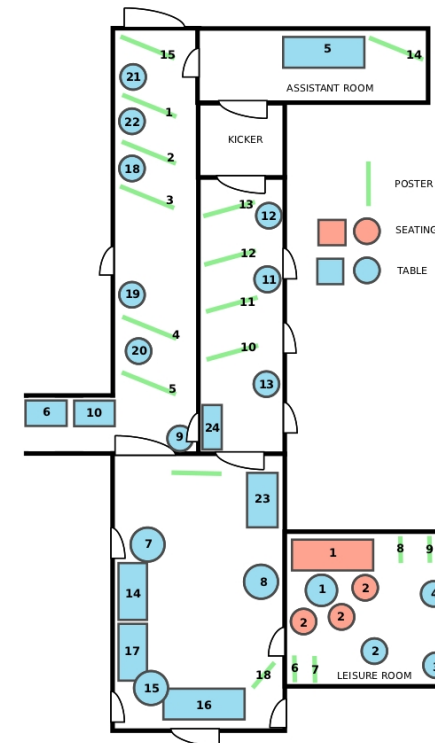
Vote-Approach



1. Determine the position (room) for user u and all his contacts with the prediction algorithm.
2. User u 's position is the majority vote among all these predictions.

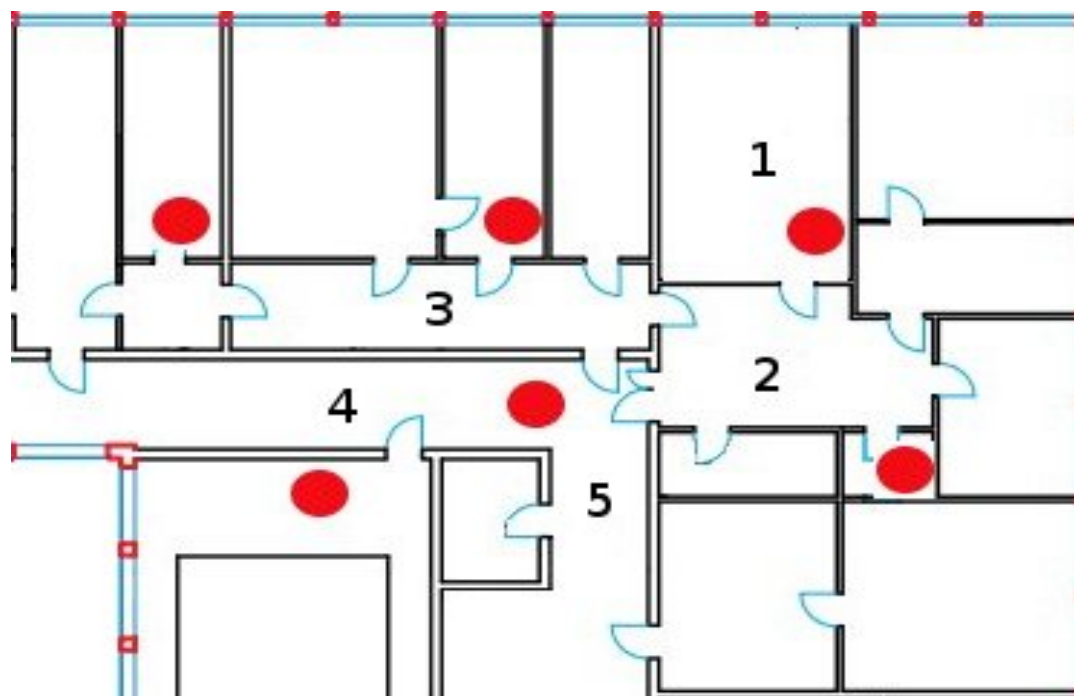


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- real-time data collected during the two hour poster-session at the LWA 2010 in Kassel.
- we asked each participant to wear a proximity tag.
- 46 people took part in our experiment.
- we placed 6 RFID readers in the conference area.

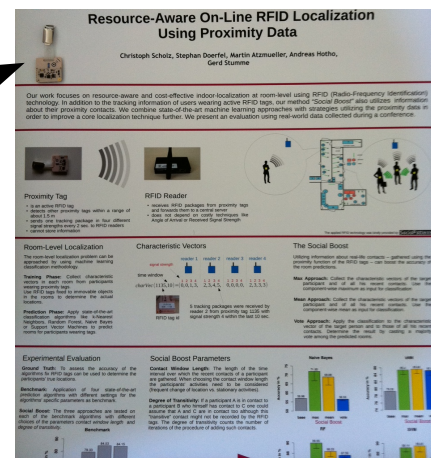


Definition: Object Tag and User Tag



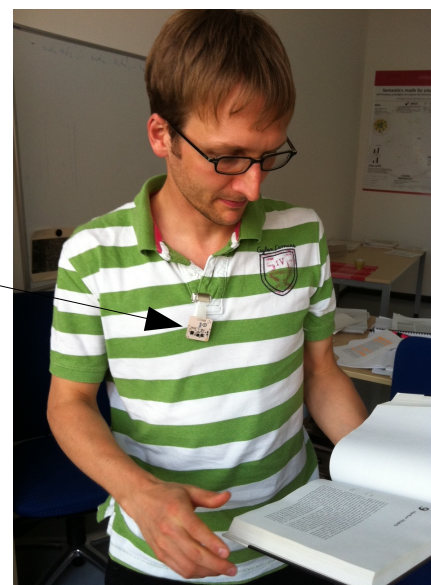
Object Tag

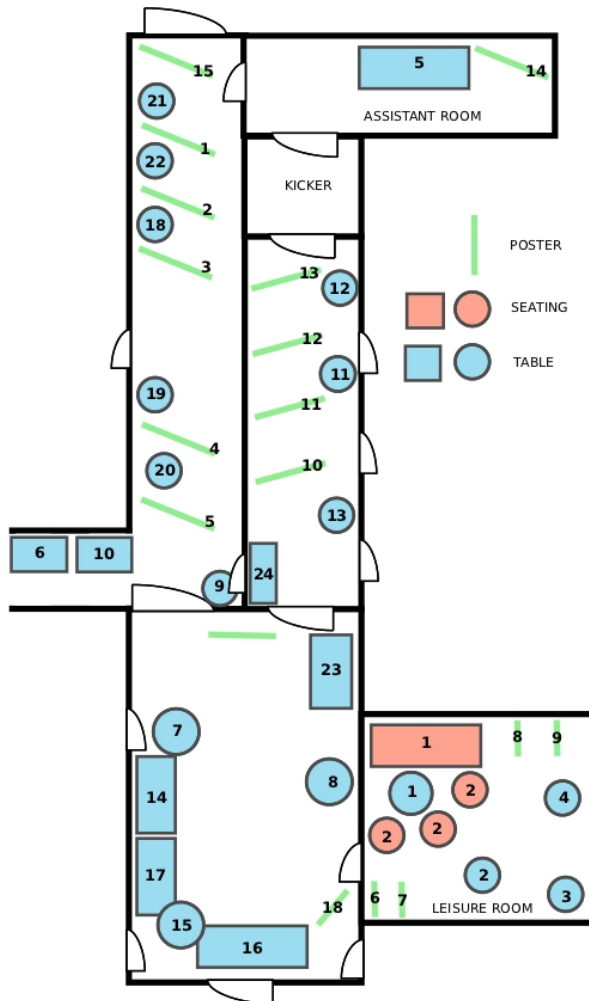
- is a proximity tag fixed to an unmovable object



User Tag

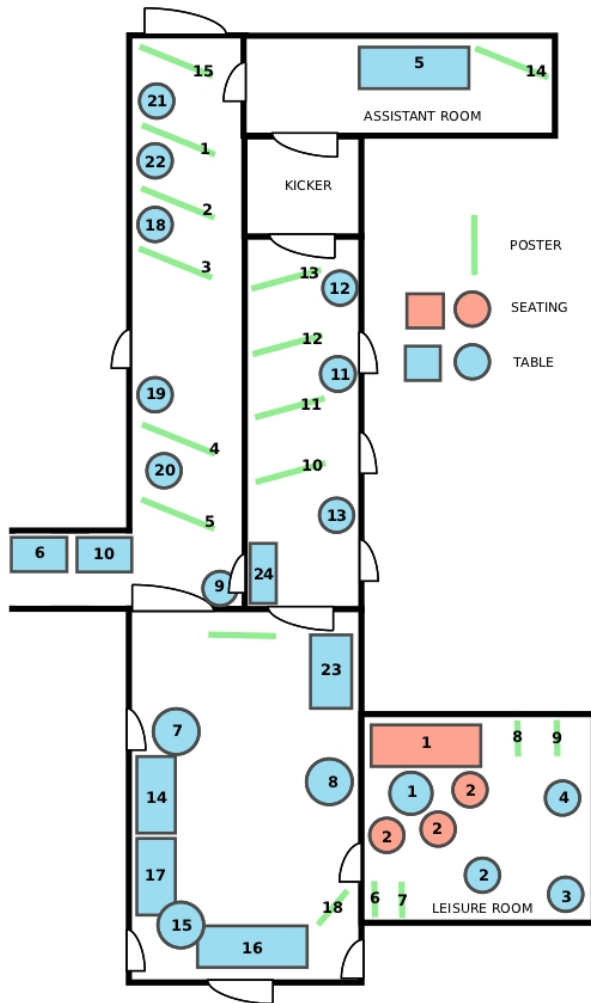
- is a proximity tag worn by a participant during the conference





- we determined the position of the participants by using object tags
- whenever a participant's tag was recorded by an object tag, we know that the participant was in the same room as the object tag
- for the experiments we predicted the rooms for the vectors where the location could be verified.

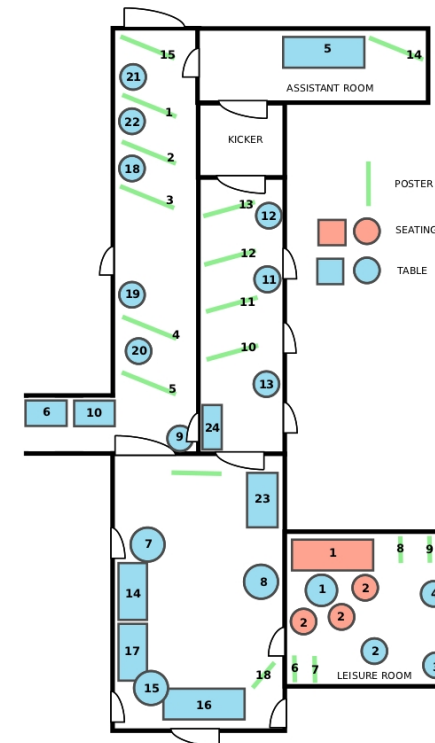
Training Data



- the first 1500 characteristic vectors collected through the object tags (ca. 20 min)



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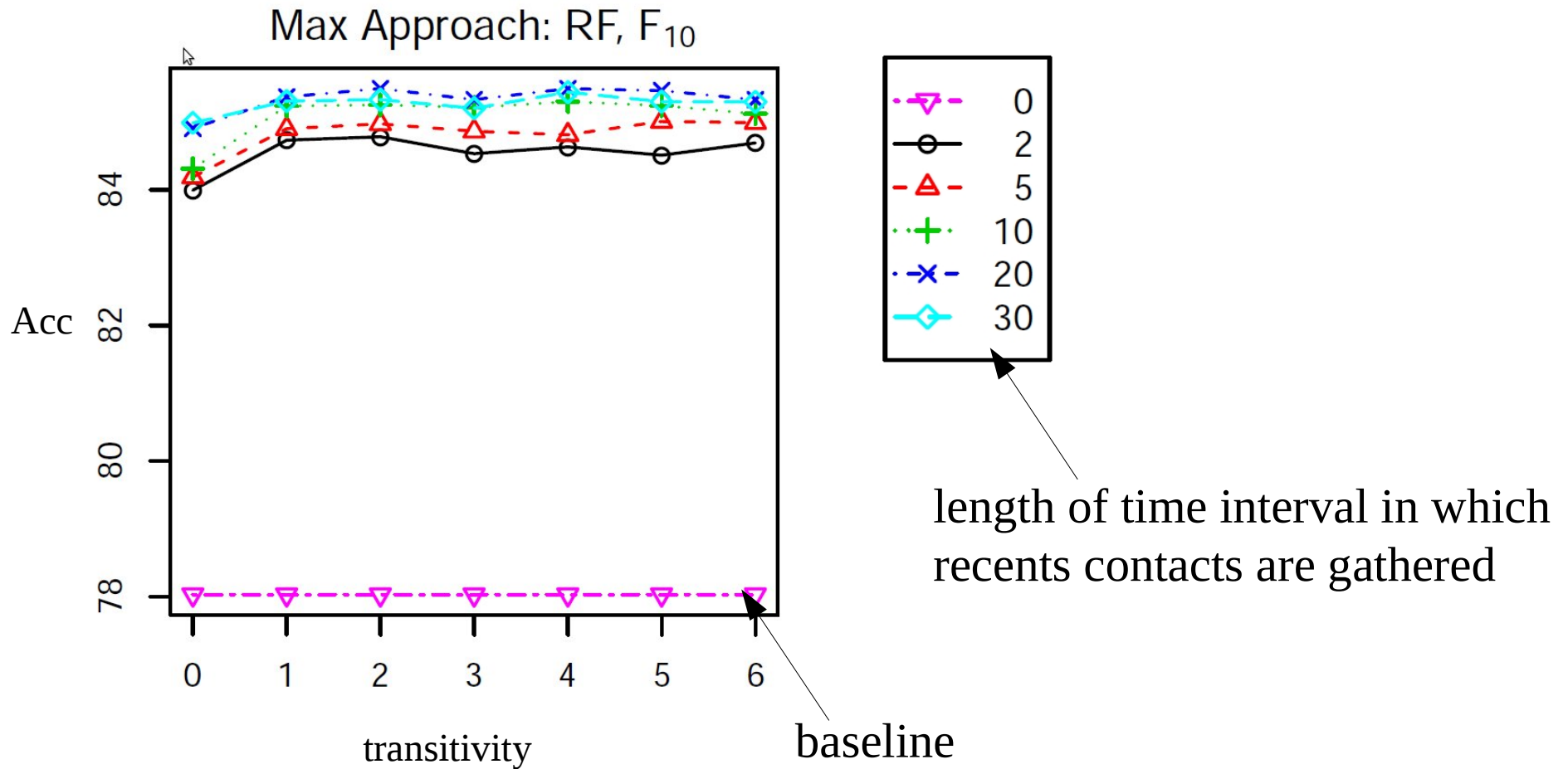


Parameters State of the Art Room Prediction



base		$l = 10$	$l = 30$	$l = 50$
kNN	k	165	185	200
	Accuracy	73.58	79.33	79.80
RF	$mtry$	1	2	4
	$ntree$	375	350	200
	Accuracy	78.03	84.18	84.78
SVM	j	1	1	1
	γ	-14	-18	-20
	Accuracy	77.95	84.15	84.84
NBAY	Accuracy	38.97	56.96	61.97

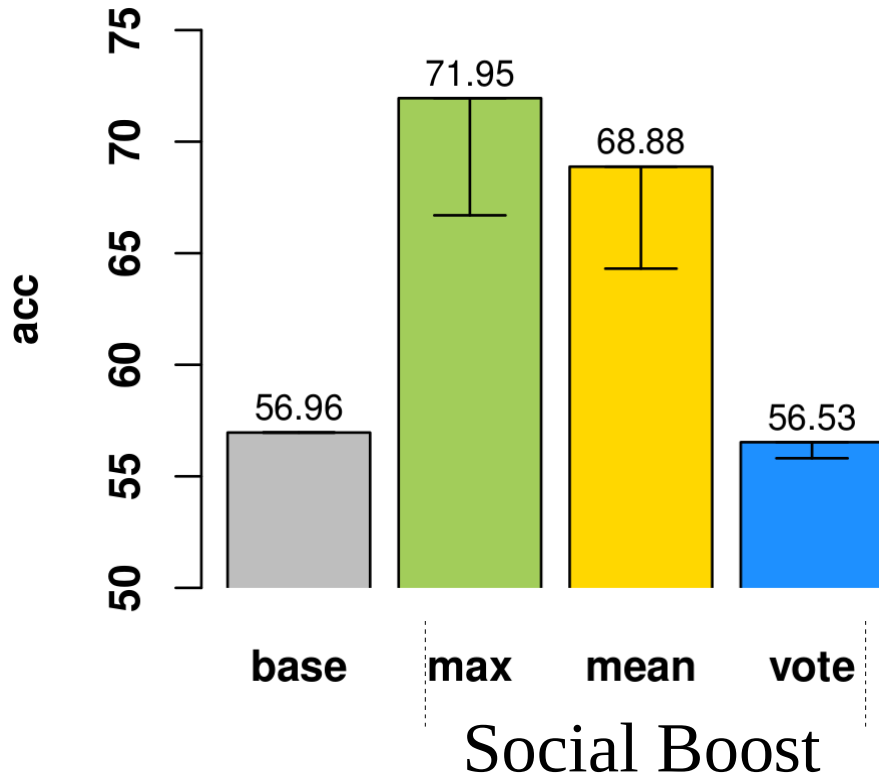
Parameters: Transitivity of Contacts



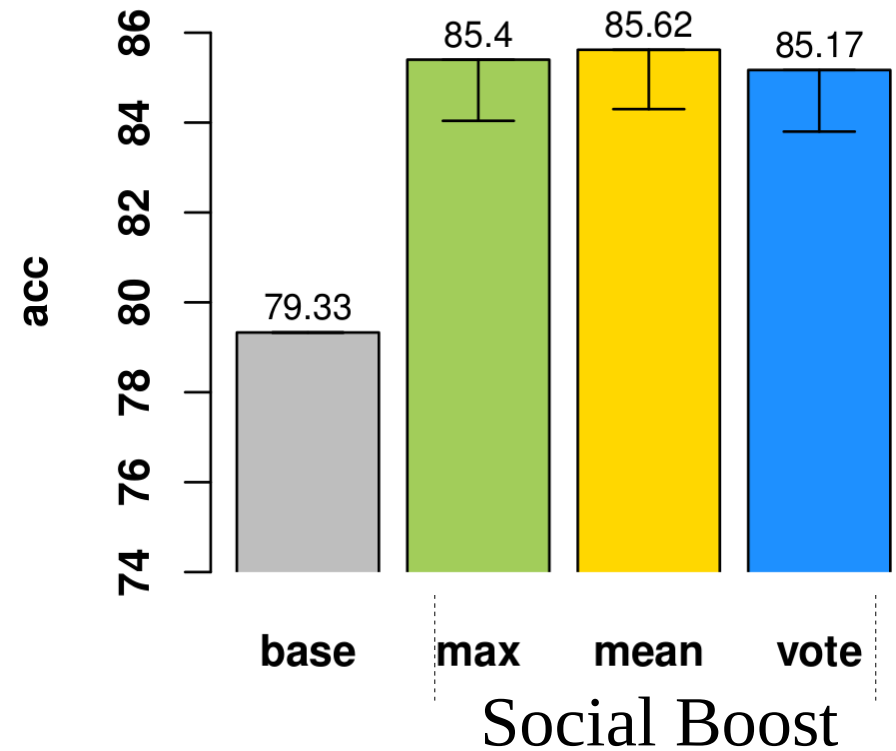
Social Boosting



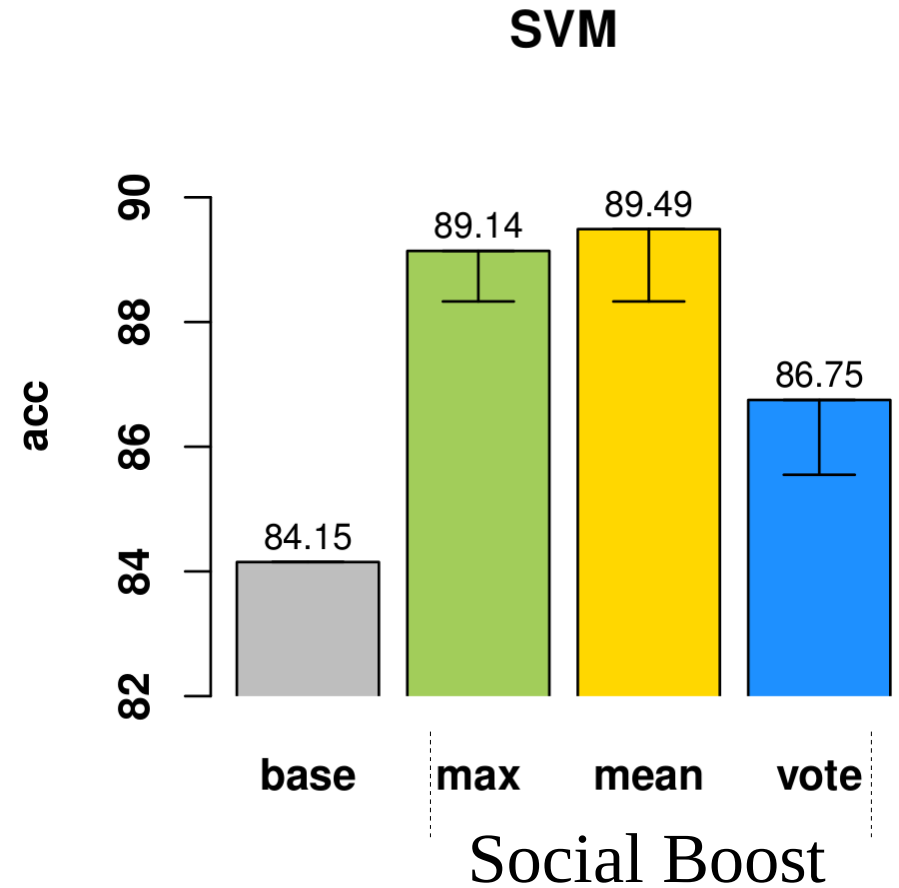
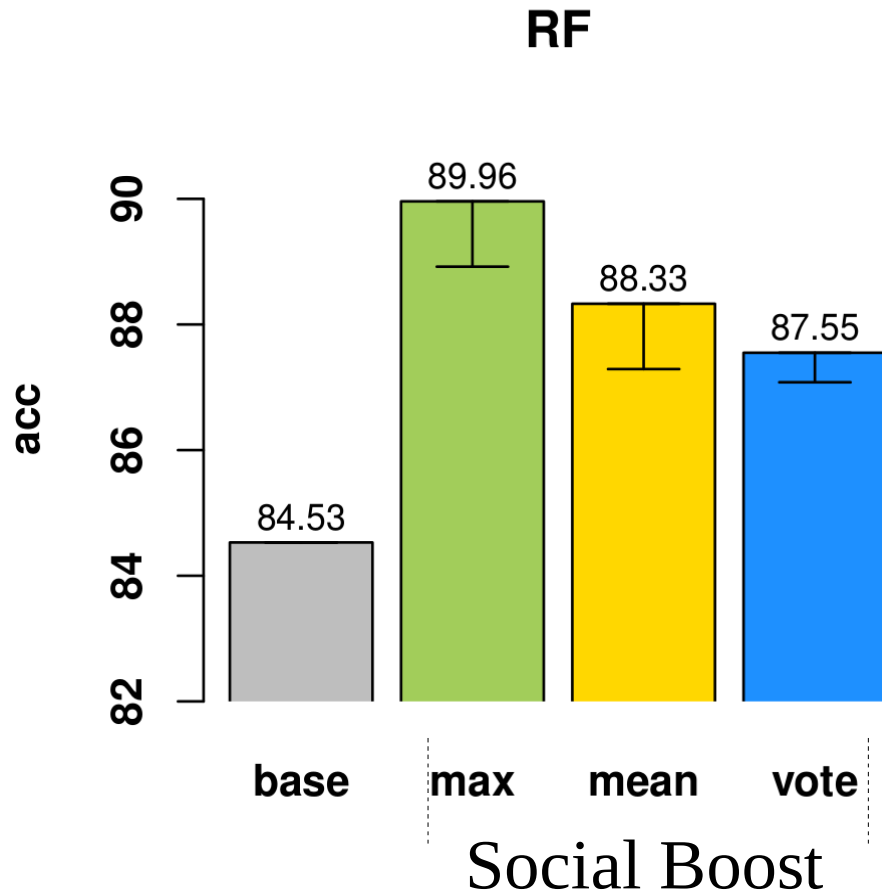
Naive Bayes

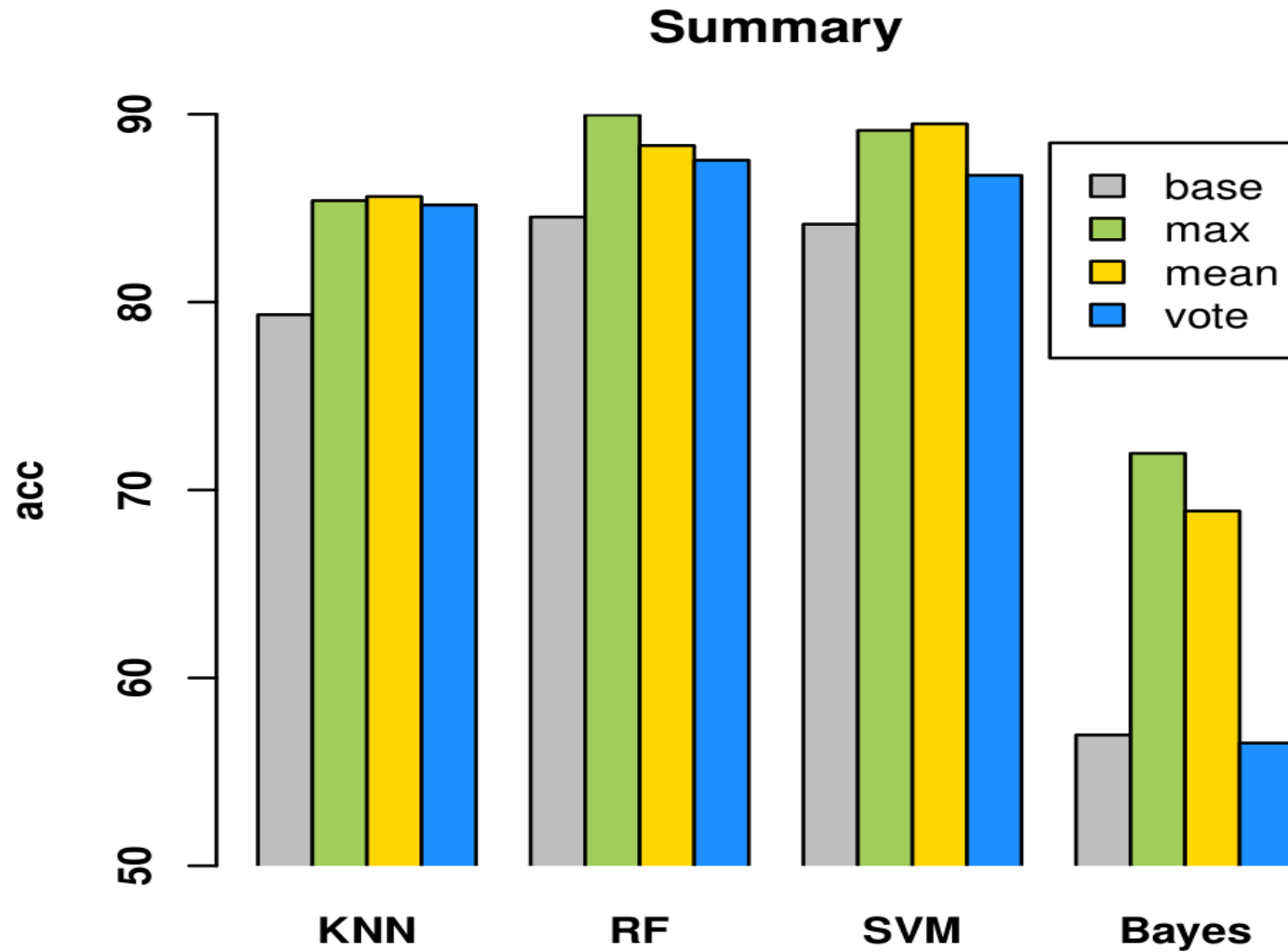


KNN



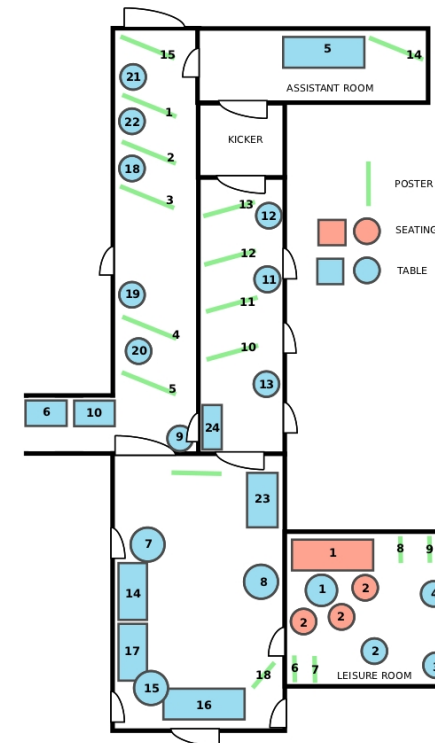
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- we presented methods that improve the localization accuracy significantly.
- RF and SVM perform very well, Naive Bayes not
- best result we got was 93 % with social boosting (only participants, who are in contact)

- learning of user data instead of object data
- using the localization history (HMM, CRFs,....)
- increasing the package frequency
- use additional datasets



Thanks for your attention.



■ BACKUP SLIDES



	kNN	RF	SVM	NBAY
strategy	F_{50}	F_{10}	F_{10}	F_{10}
contact fraction	69.23	65.01	64.91	69.3
contact base ACC	74.33	76.83	77.78	33.05
contact best ACC	88.09	88.18	89.34	58.80
boost	13.76	11.34	11.57	25.74