The Comparison of Performance, Efficiency, and Task Solution Strategies in Real, Virtual and Dual Reality Environments

Frederic Raber

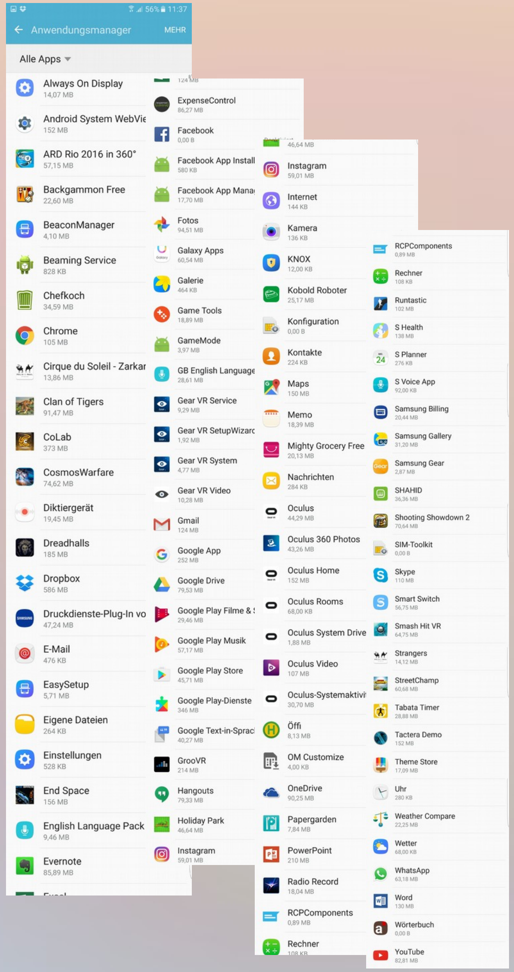
German Research Center for Artificial Intelligence

DFKI GmbH, 66123 Saarbrücken

frederic.raber@dfki.de

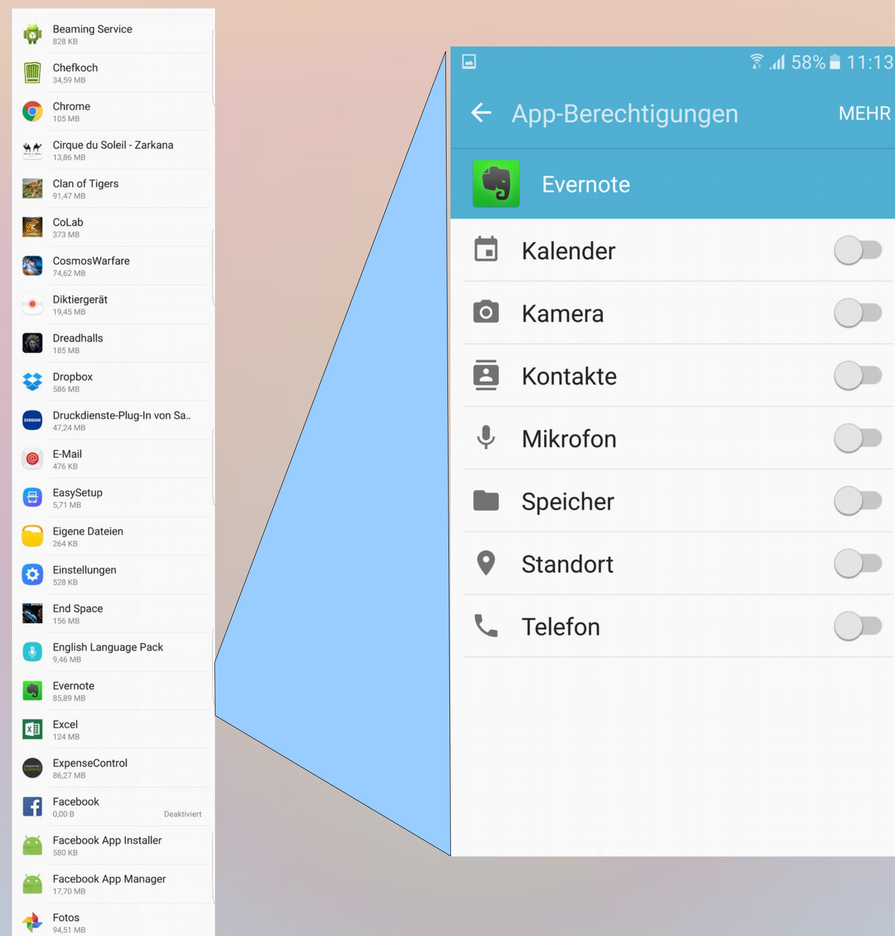
Motivation

Lots of apps on smartphones…



Motivation

…and even more permissions



Motivation

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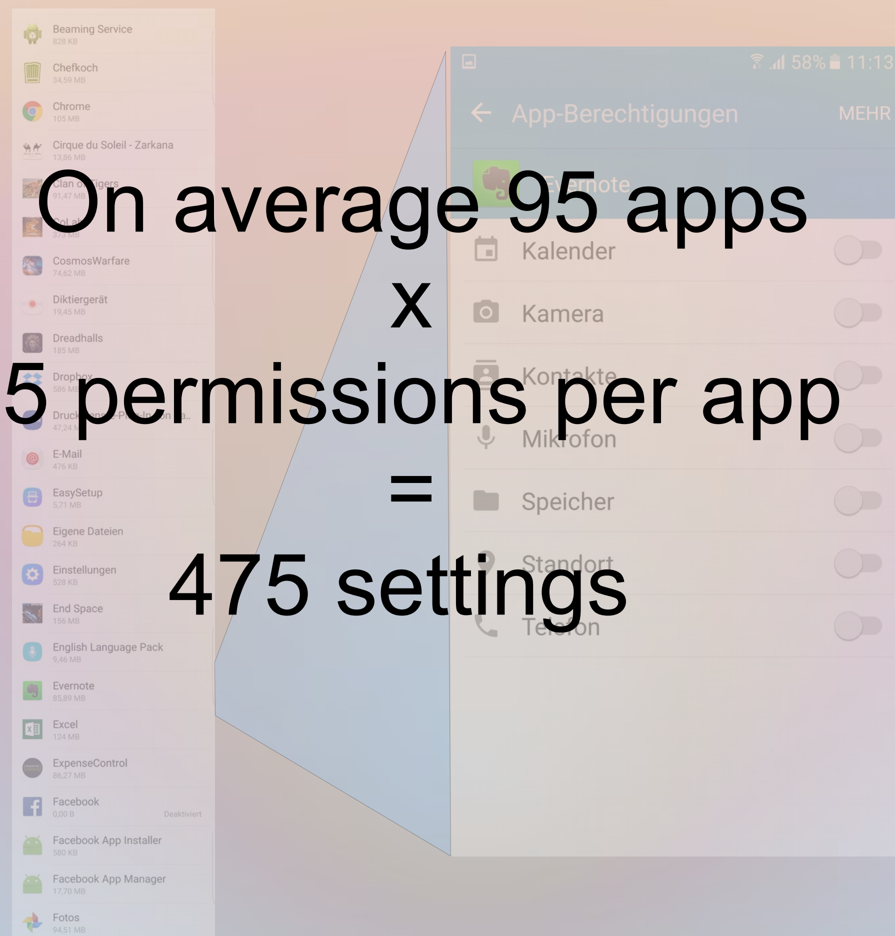


On average 95 apps

x

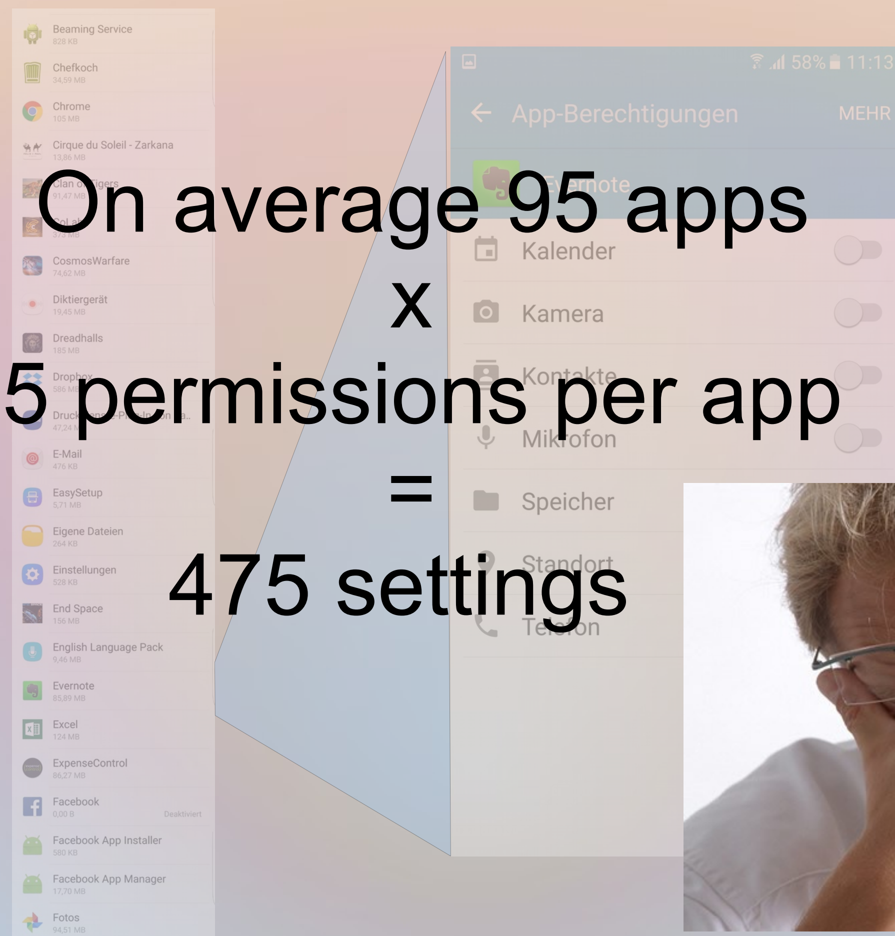
5 permissions per app

=

475 settings

Motivation

…and even more permissions



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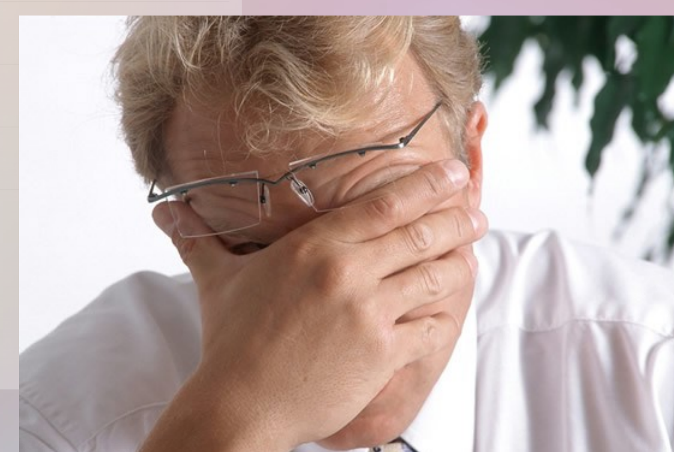


Prior Work

…in different contexts concentrated mainly on:

- Machine Learning using
  - Supervised learning,
    e.g. a friend list labeled with permissions [1]
  - Unsupervised learning based on a large online app permission database (4.8M users) and a user‘s previous sharing settings [2]
  - User feedback as additional input [3]
- Crowdsourcing [4]

Prior Work

… none of them:

- Solved the cold start problem
- Tried to draw a connection between personality, privacy attitude and app permission choice

Idea

How to capture personality?

- Capture user‘s personality

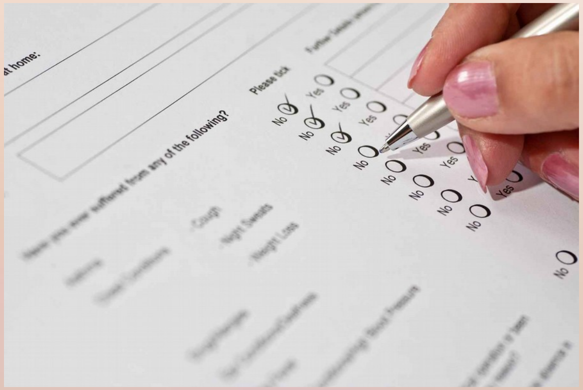
- Predict permission settings for all apps, based on the captured personality scores

Is there a correlation between personality and permission choice?

How can I do a good prediciton? Which data do I use?

Capturing Personality

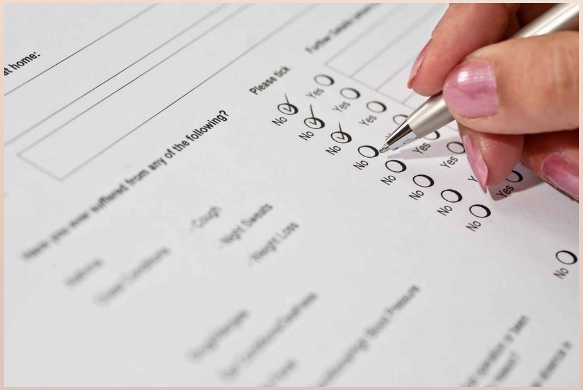
… the simple way: Questionnaire



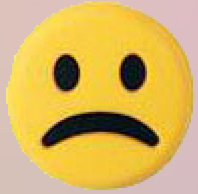
- **Big Five of Personality** (NEO-PI-R) [5] → General personality measures
- **Westin Scales** [6] → General privacy attitude
- **IUIPC** [7], **CFIP** [8] → Privacy attitude regarding (online) companies

Capturing Personality

… the simple way: Questionnaire



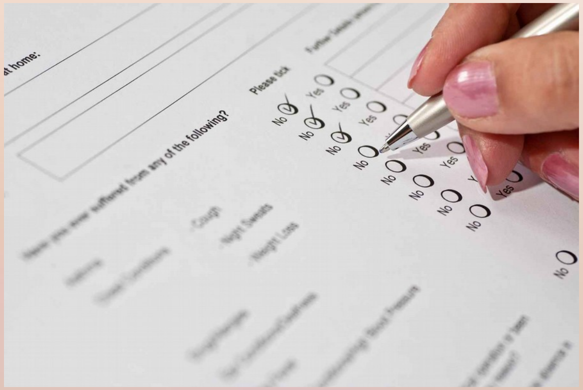
- Explicit feedback
- No side-effects
- Easy to implement
- Lots of existing questionnaires for specific domains



- Additional user burden
- Boring

Capturing Personality

… the simple way: Questionnaire



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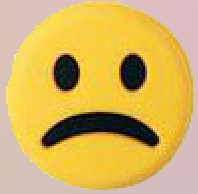
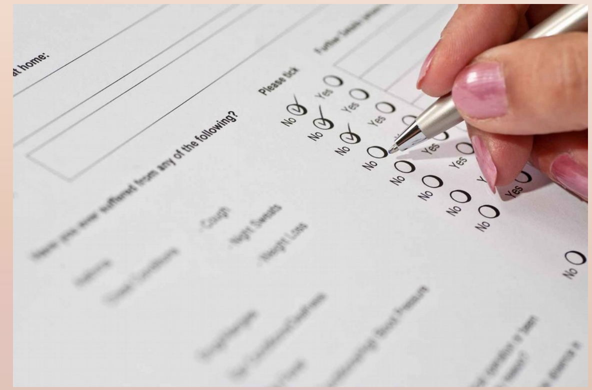


- Additional user burden
- ~~Boring~~

Gamification!

Capturing Personality

… the simple way: Questionnaire



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- No side-effects
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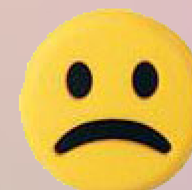


Extraction

- ~~Additional user burden~~
- ~~Boring~~

Gamification!

Capturing Personality

Extract personality measures out of written text [9]

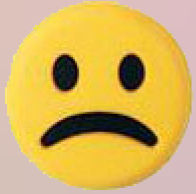
Blogs

E-Mails

Social network posts

Capturing Personality

… the harder way: Extraction



- No additional user burden

- No perfectly precise results
- Only possible for some questionnaires

Capturing Personality

… what we did: **BOTH**

- **IUIPC** to capture precise domain-specific privacy attitude
- **Big five** to capture the general personality

Capturing Personality

… what we did: **BOTH + X**

- **IUIPC** to capture precise domain-specific privacy attitude
- **Big five** to capture the general personality
- Two **extra** questions:

  „How often do you give wrong information?"

  „Have you been target of a privacy invasion frequently?"

Predictability

Predictability

Is there a correlation between personality and permission choice…?

→ Online study

- *100 participants*
- *Procedure:*
  - *IUIPC, TIPI („Big five“) + extra questions*
  - *Permission settings of ten MRU apps*

Predictability

Permission	% denied
Purchase	18.4
History	17.6
Cellular	9.5
Identity	26.6
Contacts	36.3
Calendar	16.7
Location	34.6
SMS	37.2
Phone	28.6
Photos	30.9
Camera	28.9
Microphone	25.1
Wifi	12.8
Bluetooth	5.0
ID	31.0
Other	17.9

Table 2. Percentages of denies for each app permission.

Big differences between permissions!

Predictability

Is there a correlation between personality and permission choice…?

→ it is!

			Purchase	History	Cellular	Identity	Contacts	Calendar	Location	SMS
Spearman's rho	control	Correlation Coefficient	,096	,107	,213*	-,025	,165**	,117	,143**	,020
		Sig. (2-tailed)	,150	,108	,029	,599	,001	,204	,002	,779
		N	228	227	105	433	377	120	457	196
	awareness	Correlation Coefficient	,084	,194**	,320**	,078	,140**	,205*	,112*	,113
		Sig. (2-tailed)	,206	,003	,001	,107	,007	,024	,016	,116
		N	228	227	105	433	377	120	457	196
	collection	Correlation Coefficient	,376**	,185**	,332**	,248**	,247**	,300**	,227**	,228**
		Sig. (2-tailed)	,000	,005	,001	,000	,000	,001	,000	,001
		N	228	227	105	433	377	120	457	196
	Extraversion	Correlation Coefficient	,026	,136*	,048	,119*	,028	,243**	-,073	,199**
		Sig. (2-tailed)	,693	,041	,630	,013	,594	,008	,117	,005
		N	228	227	105	433	377	120	457	196
	Agreeableness	Correlation Coefficient	,088	-,098	-,169	,000	-,046	-,106	,112*	-,056
		Sig. (2-tailed)	,184	,141	,086	,993	,371	,250	,017	,433
		N	228	227	105	433	377	120	457	196
	Conscientousness	Correlation Coefficient	,063	-,121	-,122	-,034	-,039	-,110	,142**	,029
		Sig. (2-tailed)	,343	,068	,214	,482	,453	,230	,002	,690
		N	228	227	105	433	377	120	457	196
	Emotional_Stability	Correlation Coefficient	,114	-,032	-,077	,107*	,016	,017	,179**	,080
		Sig. (2-tailed)	,087	,633	,436	,027	,752	,851	,000	,262
		N	228	227	105	433	377	120	457	196
	OpenExperiences	Correlation Coefficient	-,135*	-,171*	-,143	-,059	-,115*	-,162	-,152**	-,182*
		Sig. (2-tailed)	,042	,010	,146	,219	,026	,078	,001	,011
		N	228	227	105	433	377	120	457	196
	invasionfrequency	Correlation Coefficient	-,094	,119	,055	,121*	,039	,151	,098	,193*
		Sig. (2-tailed)	,187	,106	,625	,020	,499	,145	,057	,015
		N	199	186	81	367	306	94	374	157
	falsify	Correlation Coefficient	,100	-,123	-,276*	,044	,134*	,118	,043	,113
		Sig. (2-tailed)	,159	,094	,013	,398	,019	,256	,403	,160
		N	199	186	81	367	306	94	374	157

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

			Phone	Photos	Camera	Microphone	Wifi	Bluetooth	Wearables	ID	Other
Spearman's rho	control	Correlation Coefficient	,105	,087*	,165**	,057	,021	,108	-,097	,094	-,022
		Sig. (2-tailed)	,142	,035	,001	,364	,652	,241	,535	,101	,565
		N	196	595	370	255	462	119	43	306	666
	awareness	Correlation Coefficient	,017	,141**	,116*	,105	,077	,108	-,083	,113*	-,004
		Sig. (2-tailed)	,815	,001	,025	,094	,100	,242	,599	,049	,915
		N	196	595	370	255	462	119	43	306	666
	collection	Correlation Coefficient	,143*	,297**	,251**	,202**	,264**	,116	-,032	,283**	,127**
		Sig. (2-tailed)	,045	,000	,000	,001	,000	,211	,841	,000	,001
		N	196	595	370	255	462	119	43	306	666
	Extraversion	Correlation Coefficient	-,048	,001	,073	,076	,141**	,055	,160	,144*	,223**
		Sig. (2-tailed)	,505	,986	,164	,229	,002	,555	,305	,012	,000
		N	196	595	370	255	462	119	43	306	666
	Agreeableness	Correlation Coefficient	-,134	,086*	,109*	-,032	,040	-,001	-,019	-,046	,086*
		Sig. (2-tailed)	,062	,037	,037	,607	,390	,990	,904	,425	,026
		N	196	595	370	255	462	119	43	306	666
	Conscientousness	Correlation Coefficient	,024	,003	,013	-,029	-,021	,056	-,108	-,079	-,074
		Sig. (2-tailed)	,742	,945	,800	,649	,656	,546	,490	,169	,056
		N	196	595	370	255	462	119	43	306	666
	Emotional_Stability	Correlation Coefficient	,044	,029	-,017	,089	,079	,296**	,105	,009	,046
		Sig. (2-tailed)	,538	,477	,741	,158	,090	,001	,501	,880	,233
		N	196	595	370	255	462	119	43	306	666
	OpenExperiences	Correlation Coefficient	-,250**	-,058	-,087	-,037	,014	-,025	,186	-,127*	,088*
		Sig. (2-tailed)	,000	,159	,093	,558	,769	,784	,233	,026	,023
		N	196	595	370	255	462	119	43	306	666
	invasionfrequency	Correlation Coefficient	,046	,083	,016	,124	-,044	-,016	-,033	,017	-,150**
		Sig. (2-tailed)	,574	,069	,774	,071	,401	,884	,862	,799	,000
		N	155	485	305	214	374	85	30	237	558
	falsify	Correlation Coefficient	,101	,122**	,124*	,066	,095	-,046	-,313	,054	,055
		Sig. (2-tailed)	,211	,007	,030	,335	,067	,674	,092	,404	,197
		N	155	485	305	214	374	85	30	237	558

Predictability

Is there a correlation between personality and permission choice…?

→ ***it is!***

How can I do a good prediction?

Predictability

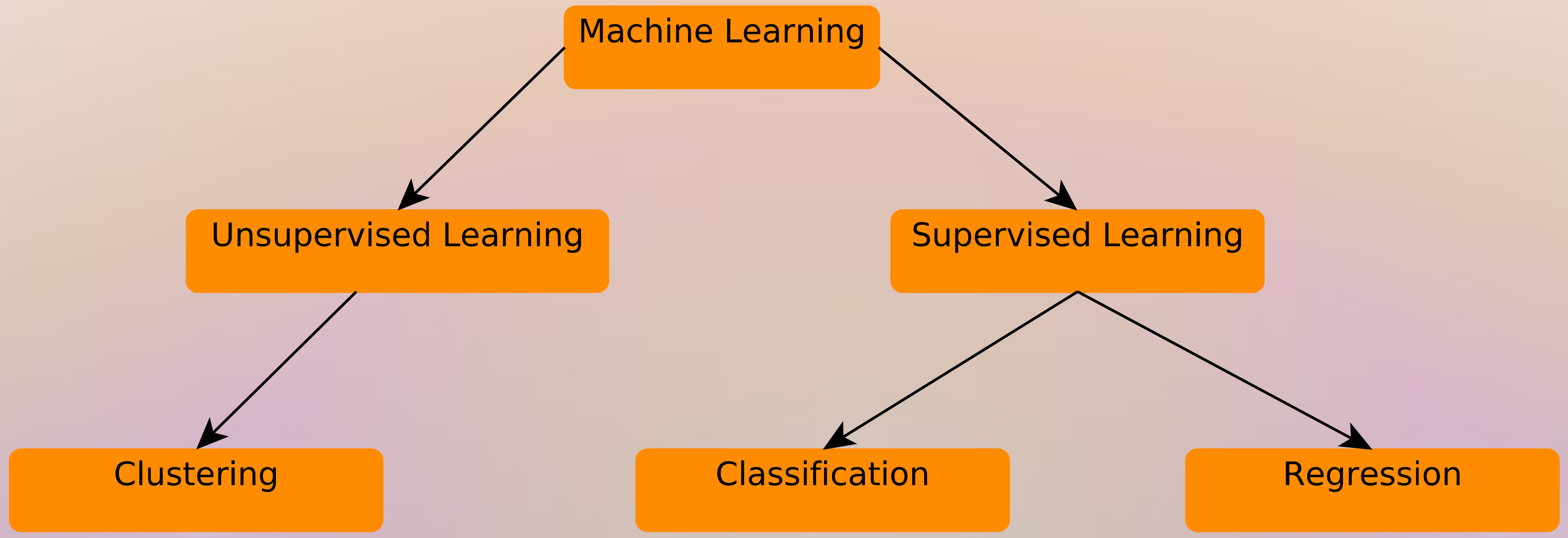
Is there a correlation between personality and permission choice…?

→ ***it is!***

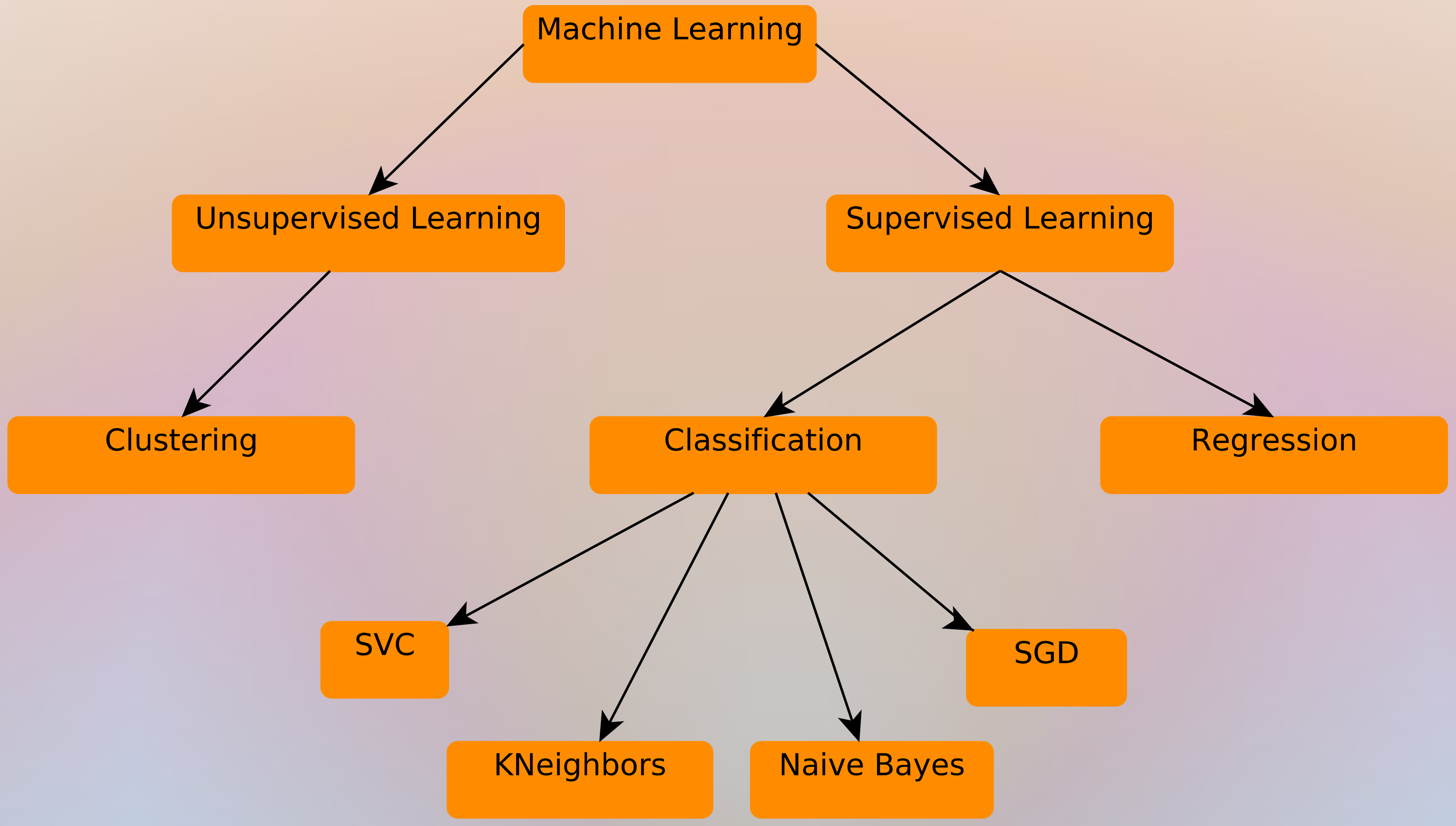
How can I do a good prediction?

→ ***Machine Learning***

Prediction


Machine Learning
Unsupervised Learning
Supervised Learning
Clustering
Classification
Regression

Prediction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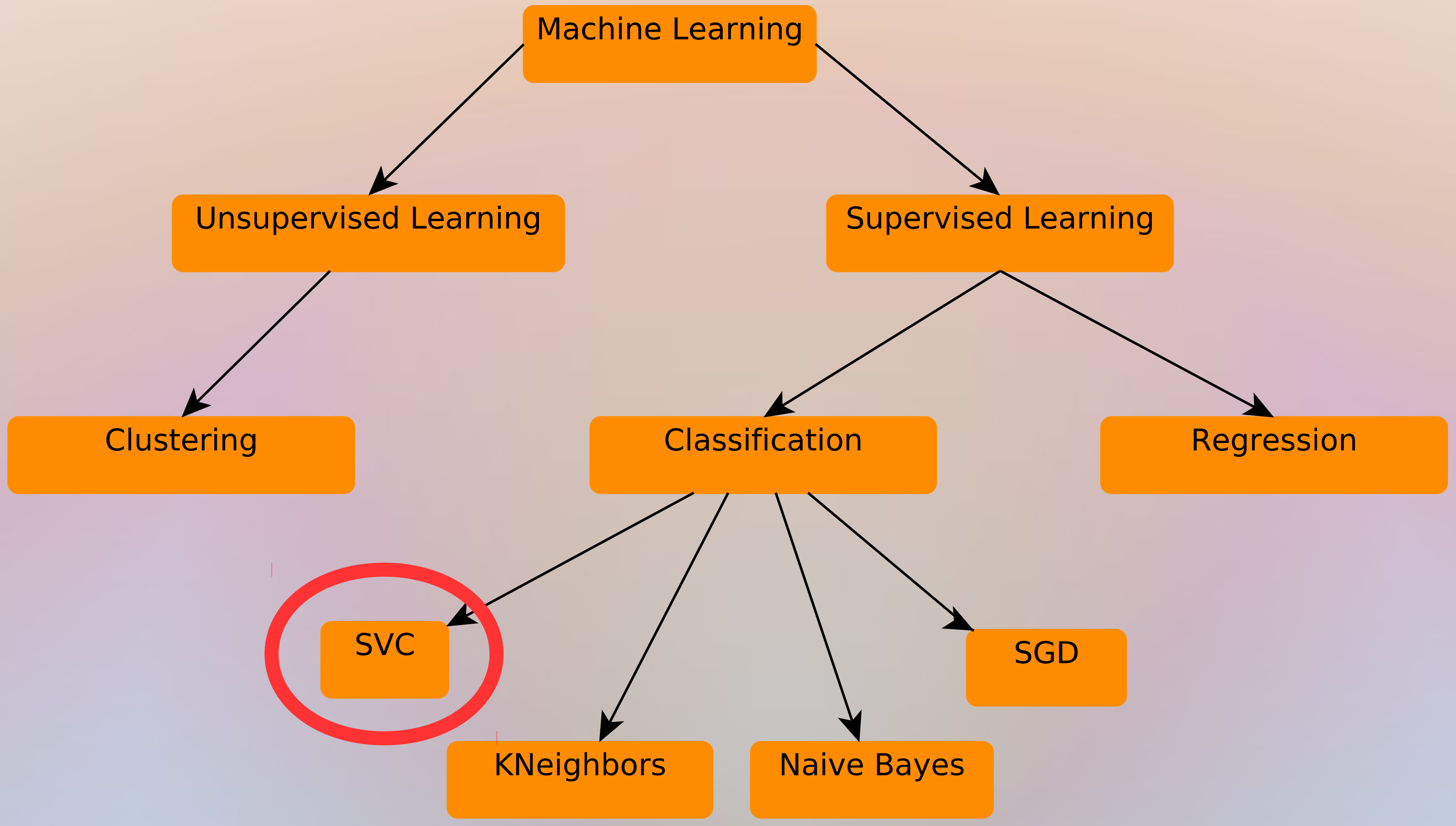
Naive Bayes

Prediction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Prediction

Input:

Answers to the privacy questionnaires:

• **IUIPC**

• **Personality** (Big Five)

• **Additional** measures

\+ **app category**

Output:

Classification (deny/allow) for each app permission

Prediction

Baseline:

Random probabilistic model based on the frequency of permission denial

→ *If a permission was denied in 80% of the cases in the study, the random probabilistic model decides with a probability of 80% to deny the permission*

Permission	% denied
Purchase	18.4
History	17.6
Cellular	9.5
Identity	26.6
Contacts	36.3
Calendar	16.7
Location	34.6
SMS	37.2
Phone	28.6
Photos	30.9
Camera	28.9
Microphone	25.1
Wifi	12.8
Bluetooth	5.0
ID	31.0
Other	17.9

Table 2. Percentages of denies for each app permission.

Prediction

Input:

Answers to the privacy questionnaires:

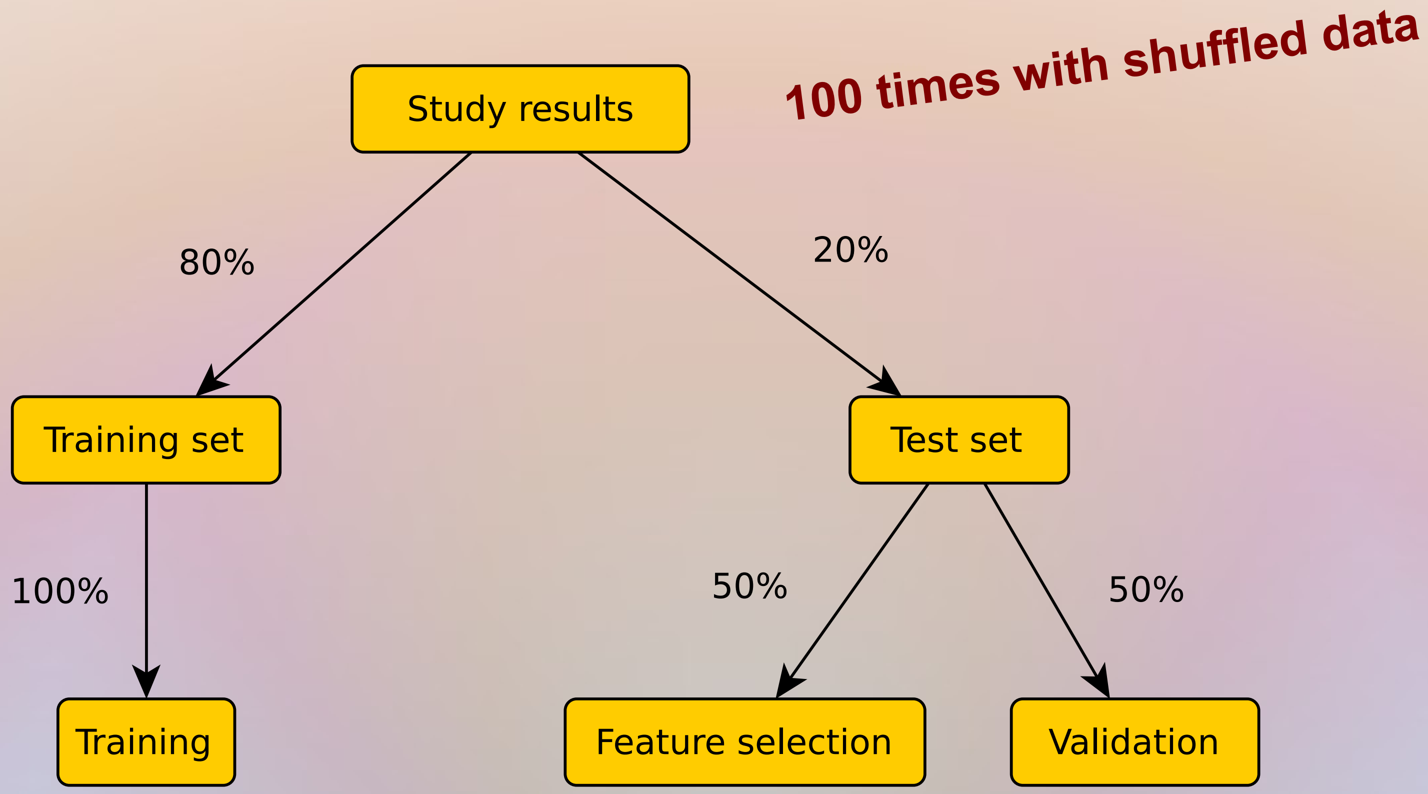
- **IUIPC**
- **Personality** (Big Five)
- **Additional** measures

\+ **app category**

Output:

Classification (deny/allow) for each app permission

Prediction


100 times with shuffled data
Study results
80%
20%
Training set
Test set
100%
50%
50%
Training
Feature selection
Validation

Prediction - Results

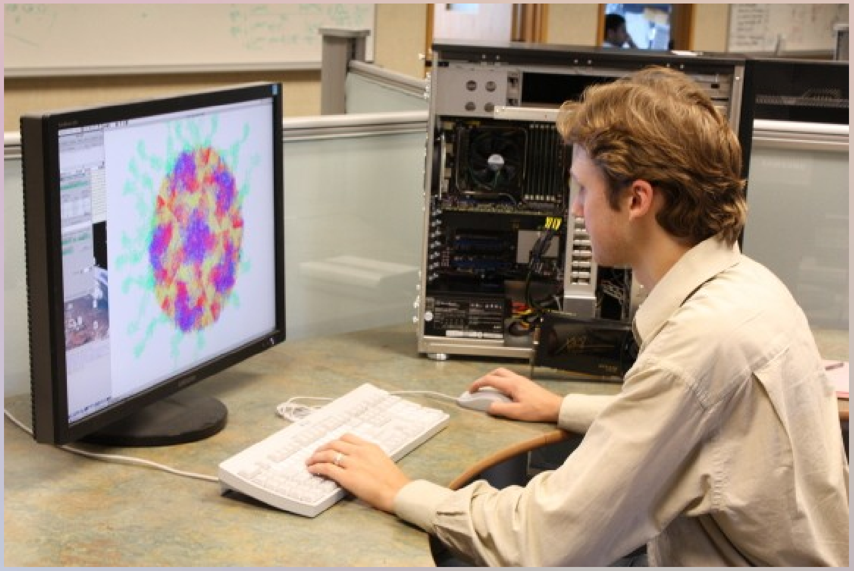
Permission	Random	IUIPC	Personality	Additional
All	59.64	70.92	69.37	70.34
Purchase	59.37	78.13	67.50	74.37
History	65.88	72.94	78.82	78.82
Cellular	78.75	92.50	91.25	90.00
Identity	51.87	68.44	60.62	63.44
Contacts	48.88	55.18	64.44	64.07
Calendar	70.00	80.00	81.11	77.77
Location	45.15	53.33	58.48	56.36
SMS	54.37	50.00	57.50	63.12
Phone	53.33	67.33	58.66	60.67
Photos	47.31	63.65	62.44	59.27
Camera	53.92	60.00	61.07	62.5
Microphone	52.50	74.00	69.00	68.00
Wifi	68.82	86.47	78.82	81.77
Bluetooth	84.44	96.66	93.33	93.33
ID	56.08	64.78	58.70	60.00
Other	63.55	71.33	68.22	72.00

Table 4. Prediction accuracy (in percent of correct predictions) for the prediction with the Random Probabilistic Model (Random), and prediction using the IUIPC questionnaire, the Big Five Personality test, or our additional questions.

Prediction – Second approach

Instead of predicting all settings in advance

→ ***Why not actively support user during his decision process?***
→ ***„Dynamic settings prediction“***



Dynamic settings prediction

How ?

			Purchase	History	Cellular	Identity	Contacts	Calendar	Location	SMS	Phone	Photos	Camera	Microphone	Wifi	Bluetooth	ID	Other
Spearman's rho	Purchase	Correlation Coefficient	1,000	,664**	,810**	,556**	,286**	.	,531**	,273	,049	,443**	,373**	,163	,484**	,375*	,346**	,428**
		Sig. (2-tailed)	.	,000	,000	,000	,005	.	,000	,064	,723	,000	,001	,231	,000	,011	,001	,000
		N	228	73	49	125	93	27	98	47	55	159	77	56	142	45	94	174
	History	Correlation Coefficient	,664**	1,000	,778**	,583**	,416**	,502**	,501**	,350**	,564**	,552**	,438**	,498**	,334**	,284*	,530**	,490**
		Sig. (2-tailed)	,000	.	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,020	,000	,000
		N	73	227	68	170	143	74	153	114	92	175	136	113	182	67	146	160
	Cellular	Correlation Coefficient	,810**	,778**	1,000	,859**	,397**	,379**	,135	,472**	,451**	,484**	,475**	,543**	,259*	.	,549**	-,099
		Sig. (2-tailed)	,000	,000	.	,000	,001	,006	,300	,001	,000	,000	,000	,000	,016	.	,000	,548
		N	49	68	105	65	71	52	61	48	59	59	50	45	86	55	55	39
	Identity	Correlation Coefficient	,556**	,583**	,859**	1,000	,556**	,344**	,455**	,419**	,506**	,467**	,413**	,595**	,401**	,354**	,605**	,408**
		Sig. (2-tailed)	,000	,000	,000	.	,000	,001	,000	,000	,000	,000	,000	,000	,000	,001	,000	,000
		N	125	170	65	433	261	93	295	157	122	369	255	193	305	91	232	361
	Contacts	Correlation Coefficient	,286**	,416**	,397**	,556**	1,000	,663**	,440**	,502**	,641**	,470**	,466**	,491**	,289**	,103	,489**	,371**
		Sig. (2-tailed)	,005	,000	,001	,000	.	,000	,000	,000	,000	,000	,000	,000	,000	,397	,000	,000
		N	93	143	71	261	377	104	275	183	158	301	245	182	244	70	197	292
	Calendar	Correlation Coefficient	.	,502**	,379**	,344**	,663**	1,000	,316**	,616**	,443**	,409**	,321**	,317*	,417**	.	,660**	,433**
		Sig. (2-tailed)	.	,000	,006	,001	,000	.	,003	,000	,001	,000	,008	,015	,000	.	,000	,000
		N	27	74	52	93	104	120	88	69	57	96	67	58	79	41	68	77
	Location	Correlation Coefficient	,531**	,501**	,135	,455**	,440**	,316**	1,000	,317**	,596**	,494**	,431**	,517**	,300**	,346**	,412**	,355**
		Sig. (2-tailed)	,000	,000	,300	,000	,000	,003	.	,000	,000	,000	,000	,000	,000	,002	,000	,000
		N	98	153	61	295	275	88	457	164	140	345	291	196	276	79	212	351
	SMS	Correlation Coefficient	,273	,350**	,472**	,419**	,502**	,616**	,317**	1,000	,713**	,423**	,337**	,409**	,311**	,191	,540**	,400**
		Sig. (2-tailed)	,064	,000	,001	,000	,000	,000	,000	.	,000	,000	,000	,000	,000	,180	,000	,000
		N	47	114	48	157	183	69	164	196	119	167	153	140	159	51	152	152
	Phone	Correlation Coefficient	,049	,564**	,451**	,506**	,641**	,443**	,596**	,713**	1,000	,543**	,421**	,304**	,217*	,357**	,598**	,378**
		Sig. (2-tailed)	,723	,000	,000	,000	,000	,001	,000	,000	.	,000	,000	,002	,011	,006	,000	,000
		N	55	92	59	122	158	57	140	119	196	147	116	102	136	57	122	143
	Photos	Correlation Coefficient	,443**	,552**	,484**	,467**	,470**	,409**	,494**	,423**	,543**	1,000	,690**	,600**	,404**	,446**	,588**	,393**
		Sig. (2-tailed)	,000	,000	,000	,000	,000	,000	,000	,000	,000	.	,000	,000	,000	,000	,000	,000
		N	159	175	59	369	301	96	345	167	147	595	319	216	357	88	254	511
	Camera	Correlation Coefficient	,373**	,438**	,475**	,413**	,466**	,321**	,431**	,337**	,421**	,690**	1,000	,703**	,455**	,167	,363**	,478**
		Sig. (2-tailed)	,001	,000	,000	,000	,000	,008	,000	,000	,000	,000	.	,000	,000	,177	,000	,000
		N	77	136	50	255	245	67	291	153	116	319	370	203	230	67	181	299
	Microphone	Correlation Coefficient	,163	,498**	,543**	,595**	,491**	,317*	,517**	,409**	,304**	,600**	,703**	1,000	,365**	,687**	,435**	,412**
		Sig. (2-tailed)	,231	,000	,000	,000	,000	,015	,000	,000	,002	,000	,000	.	,000	,000	,000	,000
		N	56	113	45	193	182	58	196	140	102	216	203	255	169	57	159	208
	Wifi	Correlation Coefficient	,484**	,334**	,259*	,401**	,289**	,417**	,300**	,311**	,217*	,404**	,455**	,365**	1,000	,642**	,382**	,510**
		Sig. (2-tailed)	,000	,000	,016	,000	,000	,000	,000	,000	,011	,000	,000	,000	.	,000	,000	,000
		N	142	182	86	305	244	79	276	159	136	357	230	169	462	105	262	353
	Bluetooth	Correlation Coefficient	,375*	,284*	.	,354**	,103	.	,346**	,191	,357**	,446**	,167	,687**	,642**	1,000	,245*	,369**
		Sig. (2-tailed)	,011	,020	.	,001	,397	.	,002	,180	,006	,000	,177	,000	,000	.	,025	,001
		N	45	67	55	91	70	41	79	51	57	88	67	57	105	119	83	73
	ID	Correlation Coefficient	,346**	,530**	,549**	,605**	,489**	,660**	,412**	,540**	,598**	,588**	,363**	,435**	,382**	,245*	1,000	,497**
		Sig. (2-tailed)	,001	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,025	.	,000
		N	94	146	55	232	197	68	212	152	122	254	181	159	262	83	306	258
	Other	Correlation Coefficient	,428**	,490**	-,099	,408**	,371**	,433**	,355**	,400**	,378**	,393**	,478**	,412**	,510**	,369**	,497**	1,000
		Sig. (2-tailed)	,000	,000	,548	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,001	,000	.
		N	174	160	39	361	292	77	351	152	143	511	299	208	353	73	258	666

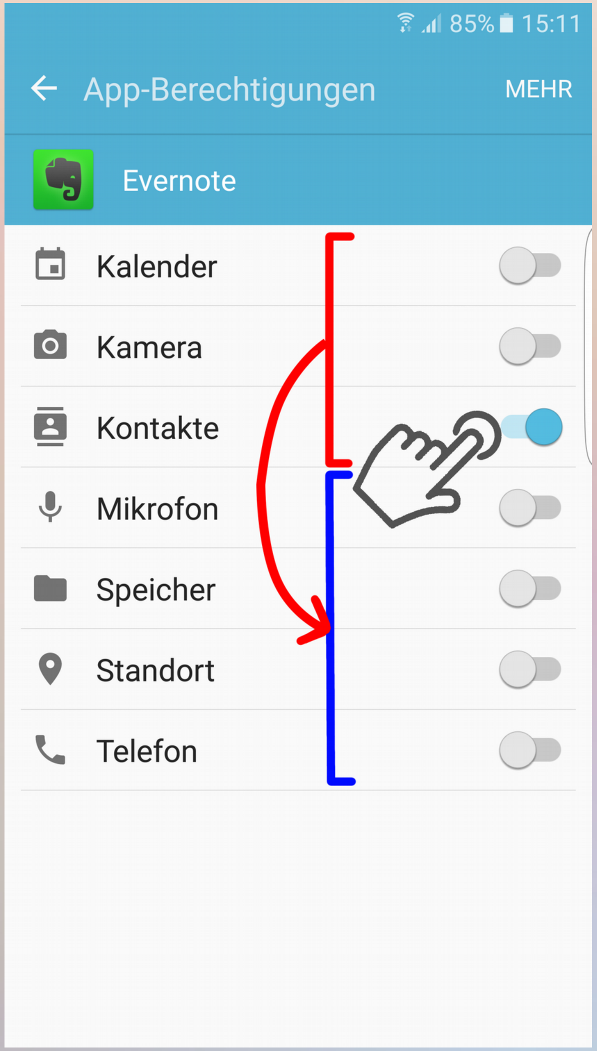
**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Dynamic settings prediction

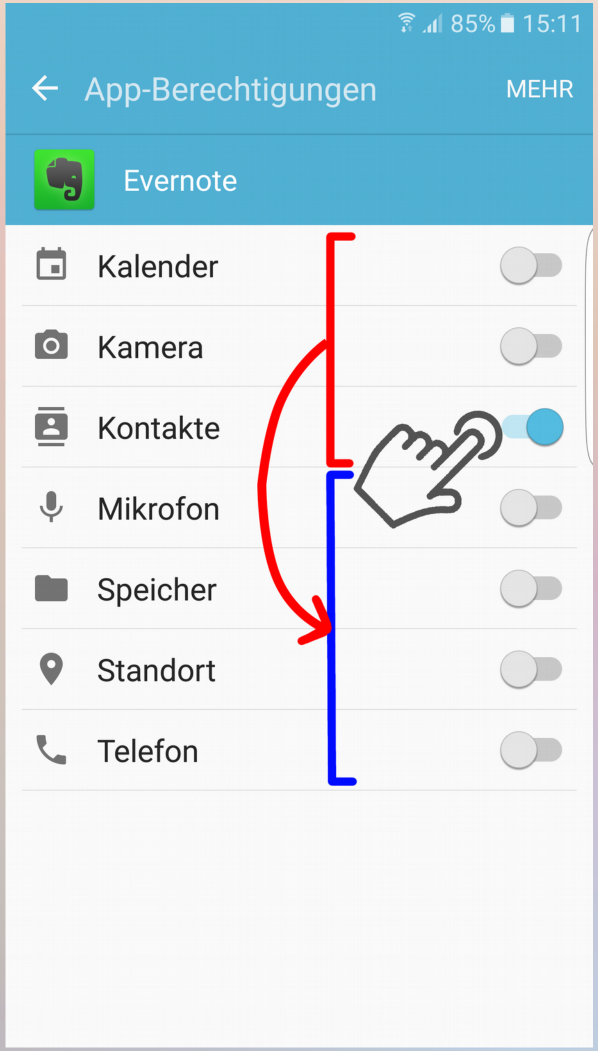
- **All settings initially set to „allow“**
- **User traverses permission list**
- **Whenever user chooses to deny a permission**

→ *Denied permission and all previous permissions used to predict remaining permissions*



Dynamic settings prediction

- Using only previous permissions
- Permissions + IUIPC
- Permissions + Personality
- Permissions + Additional measures
- Everything together



Dynamic settings prediction - Evaluation

- Same data splitting technique as for previous approach
- For each app setting in validation set, a user interaction is simulated
- Amount of „clicks“ needed is recorded
- Compared to clicks needed without dynamic prediction

```
# traverse all the user settings
for each user_settg in testset:

 # initially, all settings are
 # set to "allow"
 pred=allow_all

 for each perm in user_settg:
  if user_settg[perm]!=pred[perm]:

   # prediction was wrong,
   # user had to change the setting
   # -> predict remaining settings

   pred[perm]=user_settg[perm]
   predict_settings_below()
```

Dynamic settings prediction - Evaluation

- Using all features, **91.89%** require **less or equal** amount of clicks
- **24.66%** require **less** clicks
- Precision decreases with decreasing amount of features

Input	Won %	Draw %	Lost %	Clicks (supported)	Clicks(unsupported)
Only Permissions	23.49	59.40	17.15	1.91	2.22
IUIPC	25.76	60.60	13.63	1.83	2.21
Personality	26.58	59.30	14.12	1.70	2.10
Additional	24.48	59.90	15.62	1.84	2.14
All	24.66	67.23	8.11	1.58	2.00

Table 5. Results of the dynamic settings prediction, using only the previously selected permissions, or the permissions in addition to the IUIPC questionnaire, the Big Five Personality Score, our additional questionnaire or all previously mentioned questionnaires together.

Discussion

- Static prediction lead to significantly better results than random method
- Still, training set is small (100 users)
- Dynamic prediction often needed same amount of clicks
  → 33% of settings: Only one denied permission

Future work

- Test both approaches on users in a user study
  → Is dynamic approach accepted?
  → Which one performs better?
- In the wild study with a large user base and training set
- Explore integration of context factors into approach

Conclusion

- Setting app permission settings is cumbersome
- Two approaches for recommending permission settings:
  - **Static approach** using a questionnaire to predict all app settings a priori
  - **Dynamic approach** supporting the user during the decision process
- Both outperform the reference implementation
- Performance could be improved using a larger database
- Approaches still have to be evaluated in a user study

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