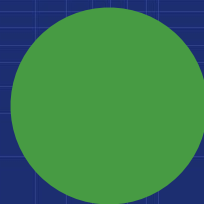
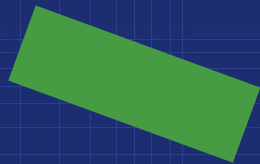






Что осталось за кадром

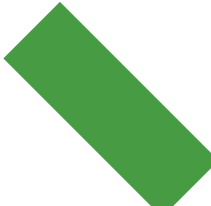



## Другие типы систем

- предсказания
    - понравится/не понравится (любым классификатором или регрессией)
  - графовые модели (community detection)
  - knowledge-based systems
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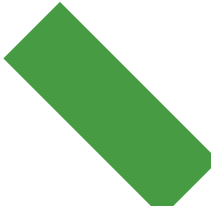

# Другие типы данных





- Графы
  - Теги
  - ...
- 
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# Гибридные системы



- Различные варианты использования нескольких систем вместе
- 
- 



# Безопасность

- Виды угроз
  - Борьба с нежелательным влиянием
  - Защита пользовательских данных
- 
- 

# Доверие

- Trust-based recommenders

# Объяснение рекомендаций

- Пользователю важно знать, почему система рекомендует тот или иной объект?
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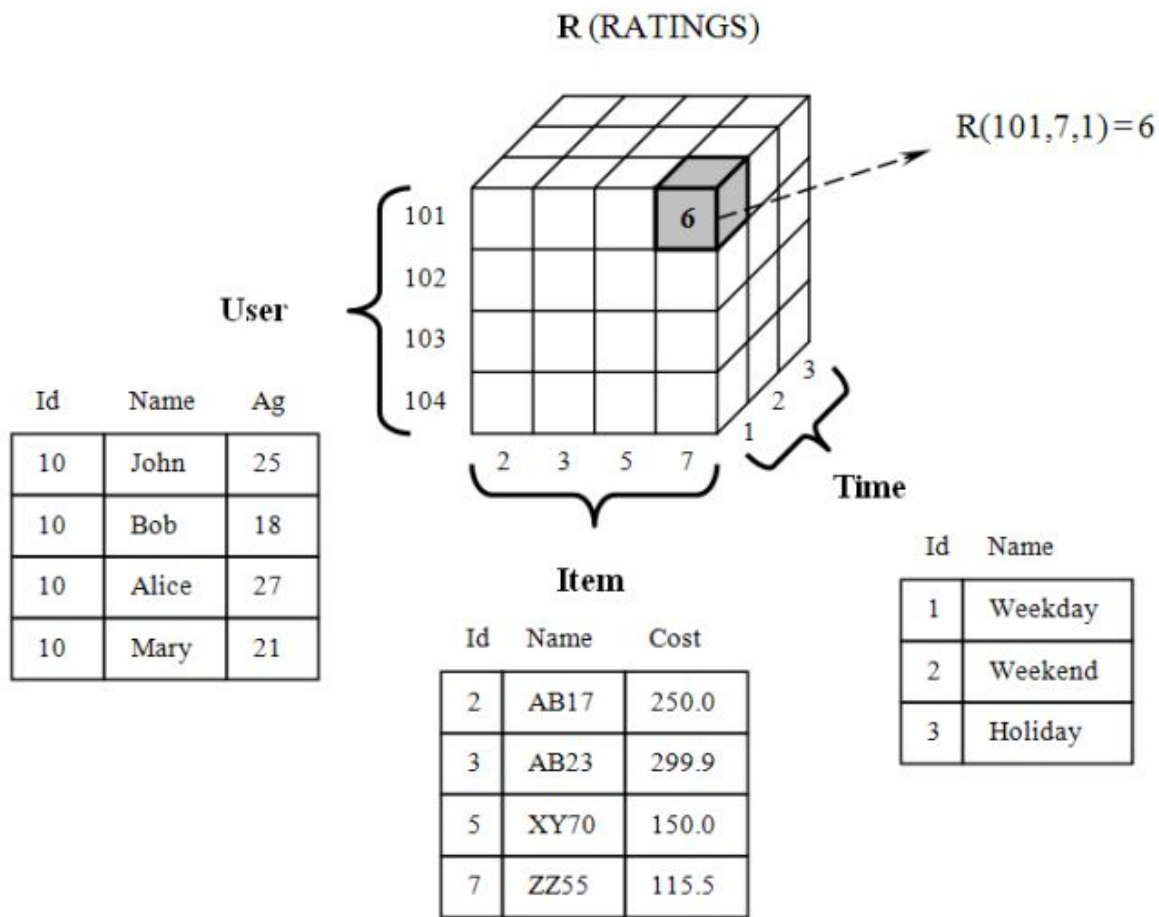
# Холодный старт

- Новый пользователь
- Новый продукт
- Новая система



# Учёт контекста

- Context-aware recommenders
- <http://ids.csom.umn.edu/faculty/gedas/NSFCareer/CARS-chapter-2010.pdf>
- [http://www.recsyswiki.com/wiki/Context-aware\\_recommendation](http://www.recsyswiki.com/wiki/Context-aware_recommendation)



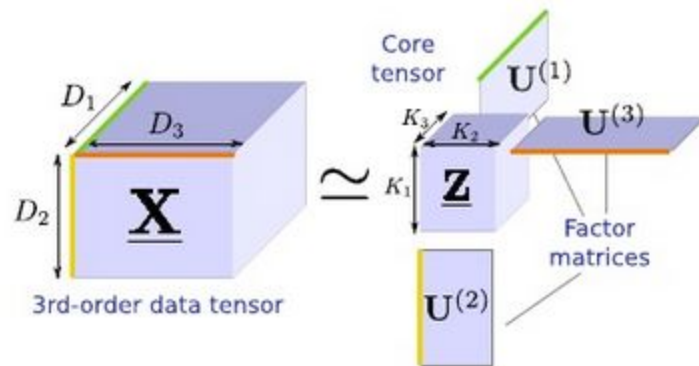
**Fig. 2** Multidimensional model for the  $User \times Item \times Time$  recommendation space.

# Tensor factorizations



- <http://www.slideshare.net/KoheiHayashi1/talk-in-jokyonokai-12989223>
- 
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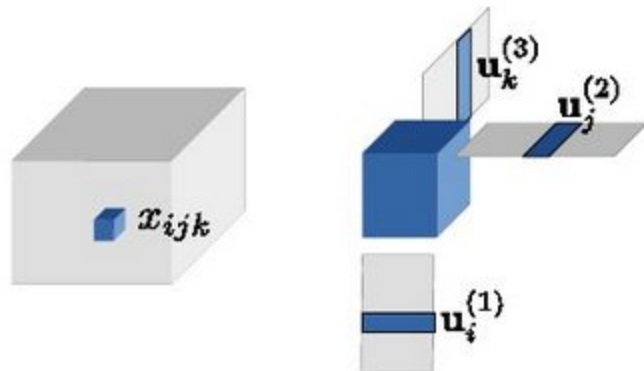
# Tucker decomposition



$$x_{ijk} = \sum_{q=1}^{K_1} \sum_{r=1}^{K_2} \sum_{s=1}^{K_3} u_{iq}^{(1)} u_{jr}^{(2)} u_{ks}^{(3)} z_{qrs} + \varepsilon_{ijk} \quad (1)$$

- $\varepsilon$ : i.i.d Gaussian noise

## Tucker decomposition





$$x_{ijk} = \sum_{q=1}^{K_1} \sum_{r=1}^{K_2} \sum_{s=1}^{K_3} \underbrace{u_{iq}^{(1)} u_{jr}^{(2)} u_{ks}^{(3)}}_{z_{qrs}} + \varepsilon_{ijk} \quad (1)$$

- $\varepsilon$ : i.i.d Gaussian noise

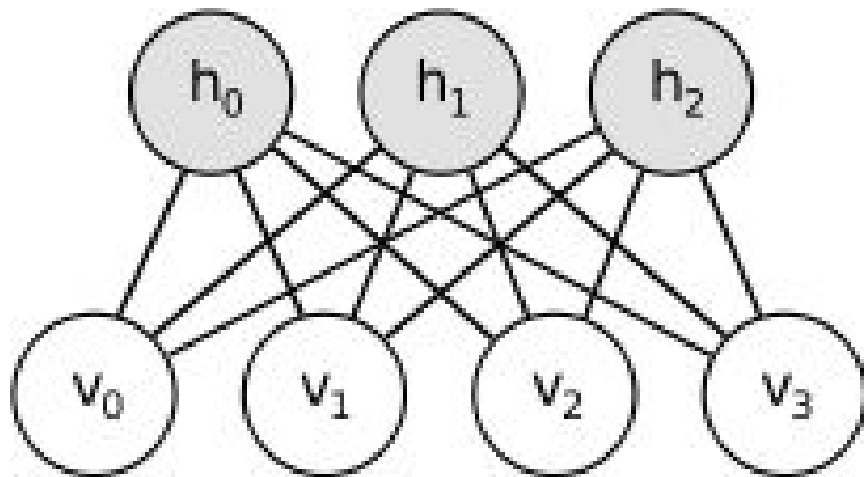
# Factorization Machines

- <http://libfm.org/>
- <http://www.slideshare.net/hongliangjie1/libfm>

Factorization machines (FM) are a generic approach that allows to mimic most factorization models by feature engineering. This way, factorization machines combine the generality of feature engineering with the superiority of factorization models in estimating interactions between categorical variables of large domain.



# Restricted Boltzmann machine (RBM)

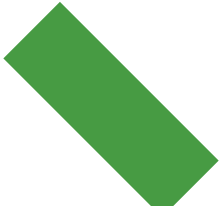



# Restricted Boltzmann machine (RBM)

- Restricted Boltzmann Machines for Collaborative Filtering  
<http://www.machinelearning.org/proceedings/icml2007/papers/407.pdf>
- “We also show that RBM’s slightly outperform carefully-tuned SVD models. When the predictions of multiple RBM models and multiple SVF models are linearly combined, we achieve an error rate that is well over 6% better than the score of Netflix’s own system”



# Restricted Boltzmann machine (RBM)

- Netflix Recommendations: Beyond the 5 stars  
<http://techblog.netflix.com/2012/04/netflix-recommendations-beyond-5-stars.html>
  - “SVD by itself provided a 0.8914 RMSE, while RBM alone provided a competitive but slightly worse 0.8990 RMSE. A linear blend of these two reduced the error to 0.88.”
- 
- 

# Deep Learning for Recommendations

- Deep learning for audio-based music recommendation  
<http://www.russia.ai/single-post/2016/12/01/Deep-learning-for-audio-based-music-recommendation>
- Spotify: <https://hackernoon.com/spotify-discover-weekly-how-machine-learning-finds-your-new-music-19a41ab76efe>
- Deep Neural Networks for YouTube Recommendations  
<https://research.google.com/pubs/pub45530.html>
- Deep learning: the future of recommendations  
<http://www.slideshare.net/balazshidasi/deep-learning-the-future-of-recommendations>
- Wide & Deep Learning for Recommender Systems  
<https://arxiv.org/abs/1606.07792>



Спасибо!

