

# How to read a Paper

ISMLL

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# Outline

How to read a paper

Common paper structure

Finding additional material

# Seminar - Advances in Deep Learning

## How to read a paper

- ▶ Like novel or newspaper stories, scientific articles need to be read differently.
- ▶ Since they are not books designed for students sometimes they are not self-contained and require some research to be fully understood.
- ▶ Understand a paper for a researcher means to be able to implement the described algorithm.

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## How to read a paper

- ▶ Skim
- ▶ Re-read
- ▶ Analyze
- ▶ Summarize

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## Skim

First get the "Big picture" by reading the title, abstract, and introduction carefully: this will tell you the major findings and why they matter.

- ▶ Quickly scan the article without taking notes: focus on headings and subheadings
- ▶ Note the publishing date and conference/journal
- ▶ Note terms and parts you don't understand.  
Only with the bigger picture you will understand how much it is necessary to investigate something.

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## Re-read

Read the article again, asking yourself questions such as:

- ▶ What problems is the study trying to solve?
- ▶ Are findings well supported by evidence?
- ▶ Is the study repeatable? (i.e. is the article self contained?)
- ▶ If you do not understand take some time to find a brief explanation of what you are not understanding (one-two sentences).
- ▶ Is the paper innovative?

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## Interpret

- ▶ Examine graphs and tables carefully
- ▶ Try to interpret data first before looking at captions
- ▶ When reading the discussion and results look after key issues and new findings
- ▶ Make sure you have distinguished the main points. If not go over the text again.

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## Summarize

- ▶ Take notes and underline key points: it improves reading
- ▶ Decide what part of the paper needs to be expanded and how much.



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## Common paper structure

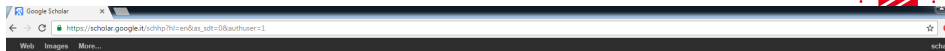
- ▶ Abstract
- ▶ Introduction
- ▶ State of the art
- ▶ Algorithms explanation
- ▶ Experiments
- ▶ Conclusions and future work
- ▶ References

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Let's take this paper as an example:

"Huang, S., Wang, S., Liu, T. Y., Ma, J., Chen, Z., and Veijalainen, J. (2015, August). **Listwise Collaborative Filtering**. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 343-352). ACM."

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## Abstract

- ▶ Brief introduction to the topic
- ▶ Brief introduction to paper achievements
- ▶ Brief summary of the experiments

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## Introduction

- ▶ Introduction to the topic
- ▶ Introduction of the main concepts
- ▶ Introduction of the main state of the art methods
- ▶ **State of the art limitations**
- ▶ **Hypotheses**
- ▶ **Contributions**

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## The Importance of Hypotheses

- ▶ It is not enough to describe some new technique or system, some claim about it must be stated and evaluated
- ▶ In experimental research, hypotheses typically take one of these two forms:
  - ▶ Technique/system X automates task Y for the first time
  - ▶ Technique/system X automates task Y better, along some dimension, than each of its rivals
- ▶ In theoretical papers, the hypotheses are the statements of theorems and the supporting evidence is their proofs

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## The Importance of Hypotheses

Technique/system X automates task Y better, along some dimension, than each of its rivals, where the dimensions are typically:

- ▶ **Behavior:** X has a higher success rate or produces better quality outputs than Y
- ▶ **Coverage:** X is applicable to a wider range of examples than Y
- ▶ **Efficiency:** X is faster or uses less space than Y
- ▶ **Dependability:** X is more reliable, safe or secure than its rivals
- ▶ **Maintainability:** X is easier to adapt and extend than its rivals
- ▶ **Usability:** Users find X easier to use than its rivals



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## State of the art / Related work

- ▶ Is a broad and shallow account of the field, which helps to place the contribution of the paper in context
- ▶ What are the rival approaches?
- ▶ What are the drawbacks of each?
  - ▶ One sentence per method. Is it clear enough?
- ▶ How has the battle between different approaches progressed?
- ▶ What are the major outstanding problems?

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## Algorithm Explanation

- ▶ First the authors introduce the algorithm from which they derived the new algorithm
- ▶ Then, the new algorithm is explained
- ▶ Contains:
  - ▶ Formulas
  - ▶ Pseudo code

**Algorithm 1:** The ListCF Algorithm

**Input:** An item set  $I$ , a user set  $U$ , and a rating matrix  $R \in \mathbb{R}^{M \times N}$ . A set of rated items  $I_u \subseteq I$  by each user  $u \in U$ . The maximal number of iterations  $maxIteration$  and error threshold  $\epsilon$ .

**Output:** A ranking  $\hat{r}_u$  of items for each user  $u \in U$ .

```

1 for  $u \in U$  do
2   for  $v \in U$  and  $u \neq v$  do
3      $P_u, P_v \leftarrow \text{TopKProDist}(I_u, I_v, R)$  /* Eq. 1 */
4      $sim(u, v) \leftarrow \text{Similarity}(P_u, P_v)$  /* Eq. 2 */
5   end
6    $N_u \leftarrow \text{SelectNeighbors}(\{sim(u, v)\}_{v \in U/u})$ 
7 end
8 for  $u \in U$  do
9    $t = 1$ 
10  repeat
11     $\epsilon = 0$ 
12    Initialize( $\varphi_u^0$ )
13    for  $g \in \mathcal{G}_k^{T_u}$  do
14       $\varphi_{u,g}^t \leftarrow \text{Update}(N_u, sim, R)$  /* Eq. 8 */
15       $\epsilon + = \sqrt{\sum (\varphi_{u,g}^t - \varphi_{u,g}^{t-1})^2}$ 
16    end
17     $t \leftarrow t + 1$ 
18  until  $t > maxIteration$  or  $\epsilon < \epsilon$ ;
19  for  $t \in T_u$  do
20     $P(t) \leftarrow \text{Aggregation}(\{\varphi_{u,g}\}_{g \in \mathcal{G}_k^{T_u}})$ 
21  end
22   $\hat{r}_u \leftarrow \text{Ordering}(\{P(t)\}_{t \in T_u})$ 
23 end

```

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## Experiments

### ▶ Dataset Explanation

- ▶ What are the available information?
- ▶ What are the available statistics? E.g. number of users, items, sparsity etc.

### ▶ Evaluation protocol

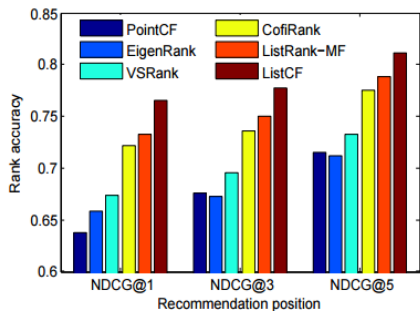
- ▶ How is the error of the algorithm computed?
- ▶ Are there any other quantitative success measures?

### ▶ Experiments

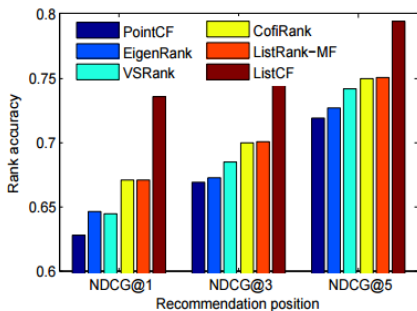
- ▶ Are the results statistically significant?

**Table 2: Statistics on the three datasets.**

	Movielens-1M	EachMovie	Netflix
#users	6,040	36,656	429,584
#items	3,952	1,623	17,770
#ratings	1,000,209	2,580,222	99,884,940
#ratings/user	165.6	70.4	232.5
#ratings/item	253.1	1589.8	5621.0
sparsity	93.7%	95.7%	98.7%



(a) Movielens-1M



(b) EachMovie

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## Conclusions

- ▶ Repeats the contributions pointing out specifically how the paper addressed it
- ▶ Include future works

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## Finding additional material

- ▶ If you don't understand something..
- ▶ This is not a book, it happens...
  - ▶ Try to pose yourself a specific questions
  - ▶ Look online



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## Finding additional material

- ▶ A book explaining the algorithms
- ▶ A PhD thesis
- ▶ Tutorials
- ▶ Highly related state of the art papers

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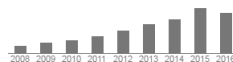
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<a href="#">Contrasting patterns of retinoblastoma protein expression in mouse embryonic stem cells and embryonic fibroblasts.</a> P Savatier, S Huang, L Szekeley, KG Wiman, J Samarut <i>Oncogene</i> 9 (3), 809-818		248	1994
<a href="#">Flooding-induced membrane damage, lipid oxidation and activated oxygen generation in corn leaves</a> B Yan, Q Dai, X Liu, S Huang, Z Wang <i>Plant and soil</i> 179 (2), 261-268		227	1996

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