

### Outline

Introduction

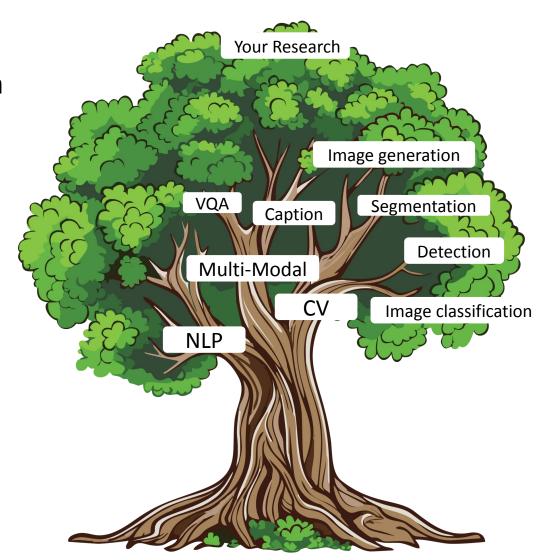
Extensive Reading

Intensive Reading

Summary

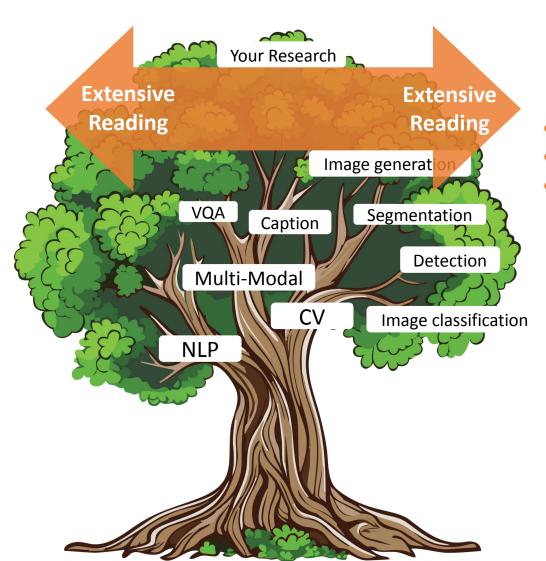
## Introduction

☐ Locate your research



### Introduction

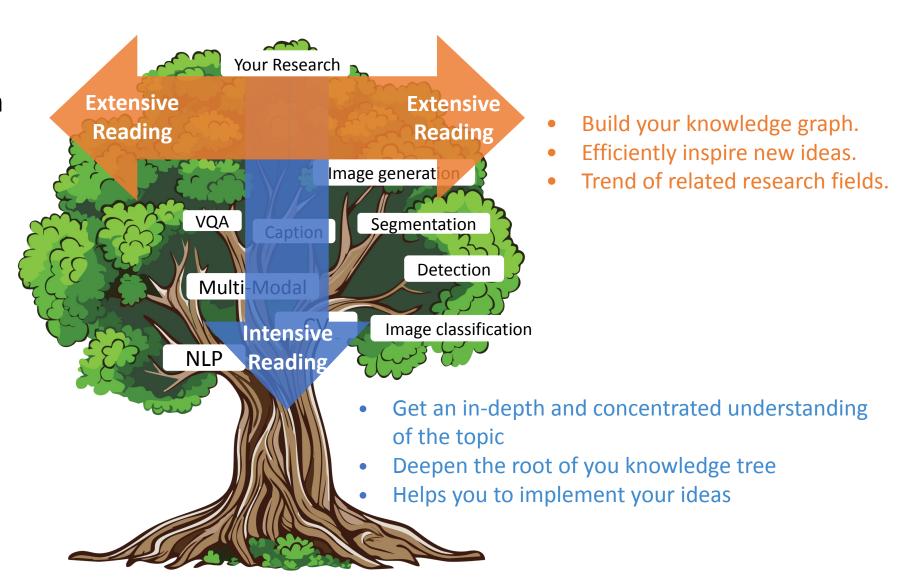
- ☐ Locate your research
- Extensive reading



- Build your knowledge graph.
- Efficiently inspire new ideas.
- Trend of related research fields.

### Introduction

- Locate your research
- Extensive reading
- Intensive reading



### Outline

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Extensive Reading

Intensive Reading

Take-away messages

■ Why to read extensively?

Build your knowledge graph. Efficiently inspire new ideas. Trend of related research fields.

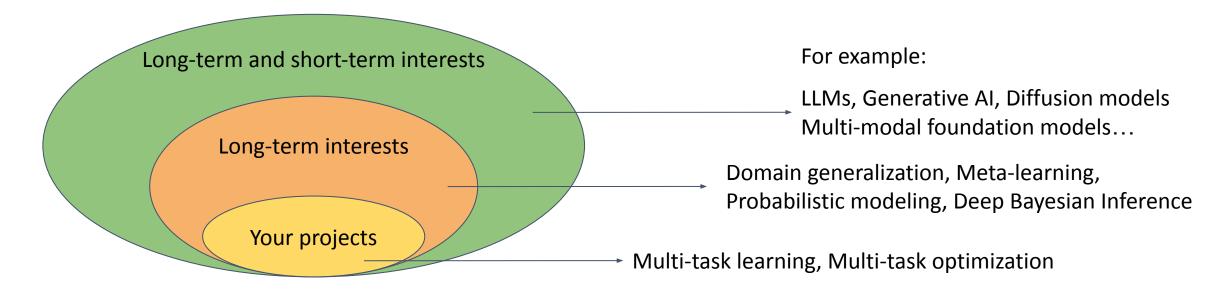
### ■ When to read extensively?

When you start your projects.
When you stuck in your projects and needs new ideas.
When you write related work for your papers.



■ What to read extensively?

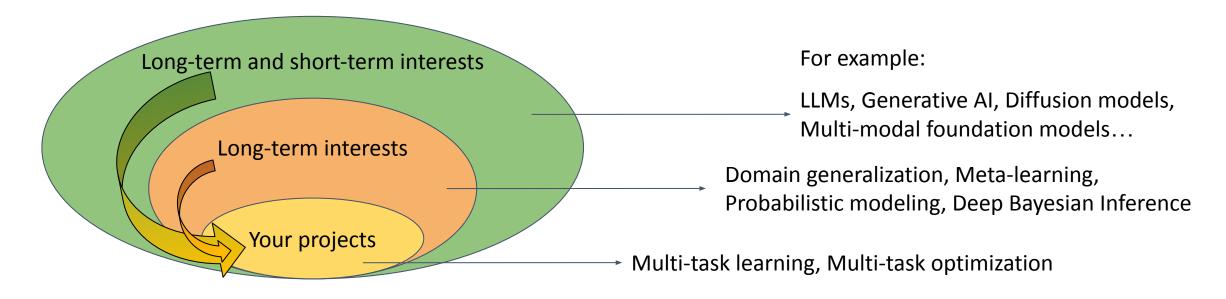
1. Choose your topics.



Interest Scope

■ What to read extensively?

1. Choose your topics.



Interest Scope

- **□** What to read extensively?
- 1. Choose your topics.
- 2. "Safari" papers based on your topics.



- What to read extensively?
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Extensive reading on your project

Extensive reading on long-term interests



Extensive reading on short-term interests

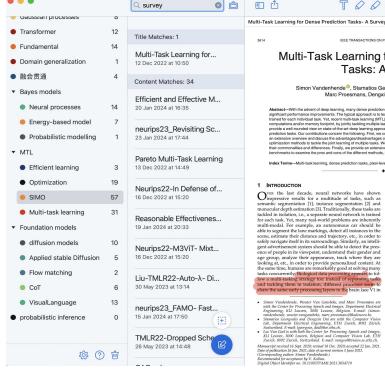
Survey papers (2~4) High-citation papers (40+, last 7~8 years) Recent papers on top-tier conferences  $(20+, last 2^3 years)$ 



**Extensive reading** on your project



Build your knowledge graph when you start a new project and write related works.



Multi-Task Learning for Dense Prediction Tasks: A Survey

T 0 0 0 9 6

Simon Vandenhende<sup>®</sup>, Stamatios Georgoulis<sup>®</sup>, Wouter Van Gansbeke<sup>®</sup>, Marc Proesmans, Dengxin Dai, and Luc Van Gool

Abstract—With the advent of deep learning, many dense prediction tasks, i.e., tasks that produce pixel-level predictions, have seen significant preferences. The typical approach is to learn these tasks in isolation, that is, a separate neural retends is trained for each individual task. Yet, recent multi-leask learning (MTL) techniques have shown promising results w.r.t. performance, computations and rot memory footprint, by jointly seaked mountiles tasks through a learned shared representation. In this survey, we powde a veill-rounded view on state-of-the-art deep learning approaches for MTL in computer vision, explicitly en ediction tasks. Our contributions concern the following. First, we consider MTL from a network architecture point setensive overview and discuss the advantages/disadvantages of recent popular MTL models. Second, we ex-

OVER the last decade, neural networks have shown Oimpressive results for a multitude of tasks, such as semantic segmentation [1], instance segmentation [2] and monocular depth estimation [3]. Traditionally, these tasks are tackled in isolation, i.e., a separate neural network is trained for each task. Yet, many real-world problems are inherently multi-modal. For example, an autonomous car should be able to segment the lane markings, detect all instances in the scene, estimate their distance and trajectory, etc., in order to safely navigate itself in its surroundings. Similarly, an intelli-gent advertisement system should be able to detect the pres-ence of people in its viewpoint, understand their gender and age group, analyze their appearance, track where they are looking at, etc., in order to provide personalized content. At the same time, humans are remarkably good at solving many tasks concurrently. Biological data processing appears to follow a multi-tasking strategy too: instead of separating tasks and tacking them in solation, different processes seem to

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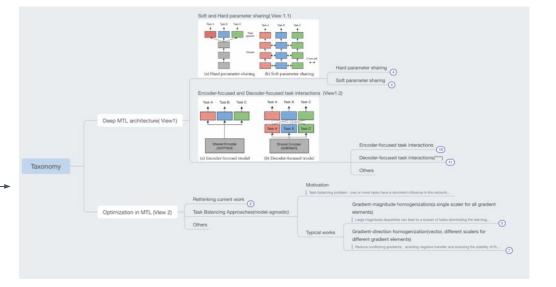
escript received 16 Sept. 2020; revised 18 Dec. 2020; accepted 22 Jan. 2021. of publication 26 Jan. 2021; date of current version 3 June 2022.

vated researchers to develop generalized deep learning mod

els that given an input can infer all desired task outputs.

Multi-Task Learning (MTL) [30] aims to improve such ger tained in the training signals of related tasks. In the deer individual task is solved separately by its own network, suc multi-task networks bring several advantages to the table. First, due to their inherent layer sharing, the resulting mem-

Score. In this survey, we study deep learning approache for MTL in computer vision. We refer the interested reade to [31] for an overview of MTL in other application domains emphasize on solving multiple pixel-level or dense prediction tasks, rather than multiple image-level classification tasks, a case that has been mostly under-explored in MTL. Tackling multiple dense prediction tasks differs in several aspects from solving multiple classification tasks. First, as jointly learning multiple dense prediction tasks is governed by the use of different loss functions, unlike classification tasks that mostly use cross-entropy losses, additional consideration is required to avoid a scenario where some tasks overwhelm the others during training. Second, opposed to image-level classification tasks, dense prediction tasks can not be directly



High-citation papers (20+, last 7~8 years)
Recent papers on top-tier conferences
(10+, last 2~3 years)

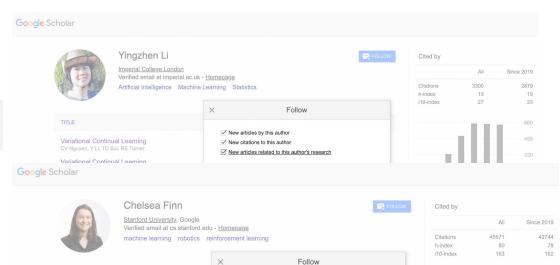




Extensive reading on long-term interests



Efficiently inspire new ideas when you stuck in your projects.



New articles by this author

✓ New citations to this author✓ New articles related to this author's research

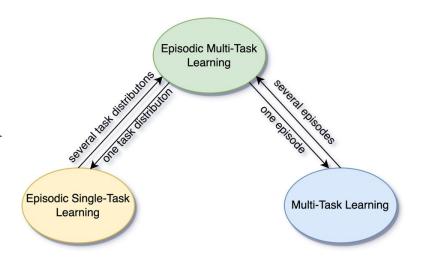
Email address for updates

j.shen@uva.nl

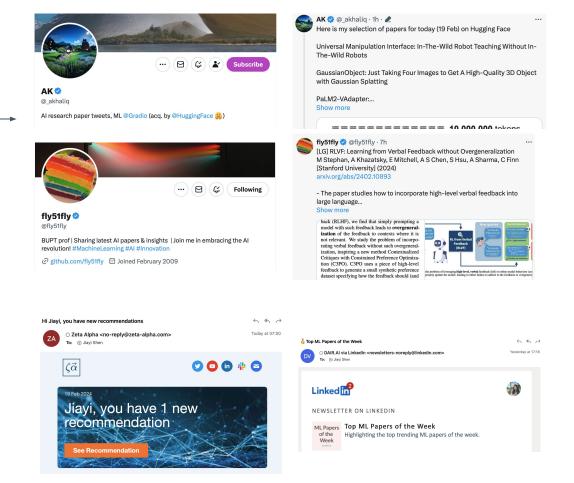
Model-agnostic meta-learning for fast adaptation

End-to-end training of deep visuomotor policies

On the opportunities and risks of foundation mode







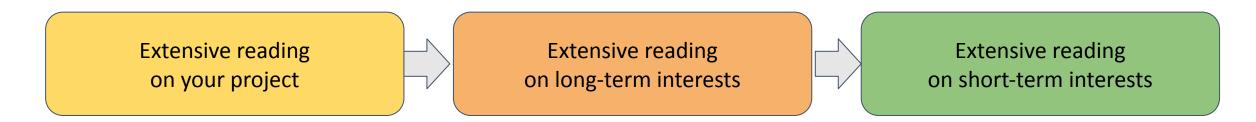
Trend of related research fields,

preparations for your future work

Building habits (once a week, about ten papers)

Job hunting, Social impacts, Potential collaborations.

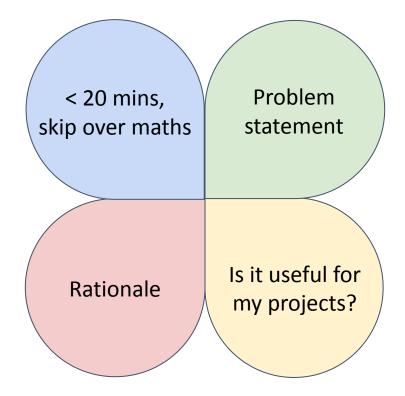
- What to read extensively?
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☐ How to read extensively?

☐ How to read extensively?

After the paper "safari", you probably know its title/abstract/main figures.



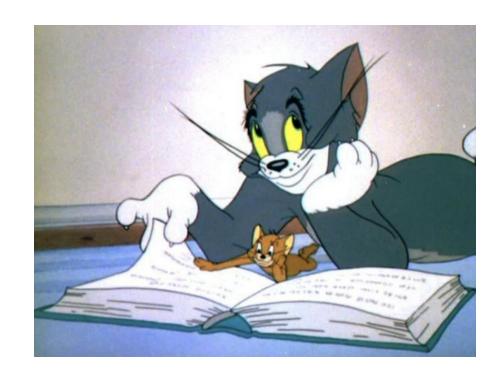
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Extensive Reading

Intensive Reading

Summary



Tom and Jerry Reading – if only scientific journals were as fun!

# **Intensive Reading**

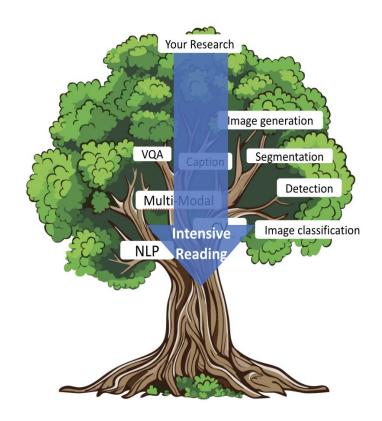
reading in detail with specific learning aims and tasks

### **□** Why to read intensively?

get an in-depth and concentrated understanding of the topic deepen the root of you knowledge tree helps you to implement your ideas

### **□** When to read intensively?

when you have gained an overall understanding of the topic when you narrowed down your research topic when you want to re-implement other's research or improve their results



# How to read Intensively



# read the paper in three passes

### How to Read a Paper

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### **ABSTRACT**

Researchers spend a great deal of time reading research papers. However, this skill is rarely taught, leading to much wasted effort. This article outlines a practical and efficient three-pass method for reading research papers. I also describe how to use this method to do a literature survey.

Categories and Subject Descriptors: A.1 [Introductory and Survey]

General Terms: Documentation. Keywords: Paper, Reading, Hints.

### 1. INTRODUCTION

Researchers must read papers for several reasons: to review them for a conference or a class, to keep current in their field, or for a literature survey of a new field. A typical researcher will likely spend hundreds of hours every year reading papers.

Learning to efficiently read a paper is a critical but rarely taught skill. Beginning graduate students, therefore, must learn on their own using trial and error. Students waste much effort in the process and are frequently driven to frustration.

For many years I have used a simple approach to efficiently

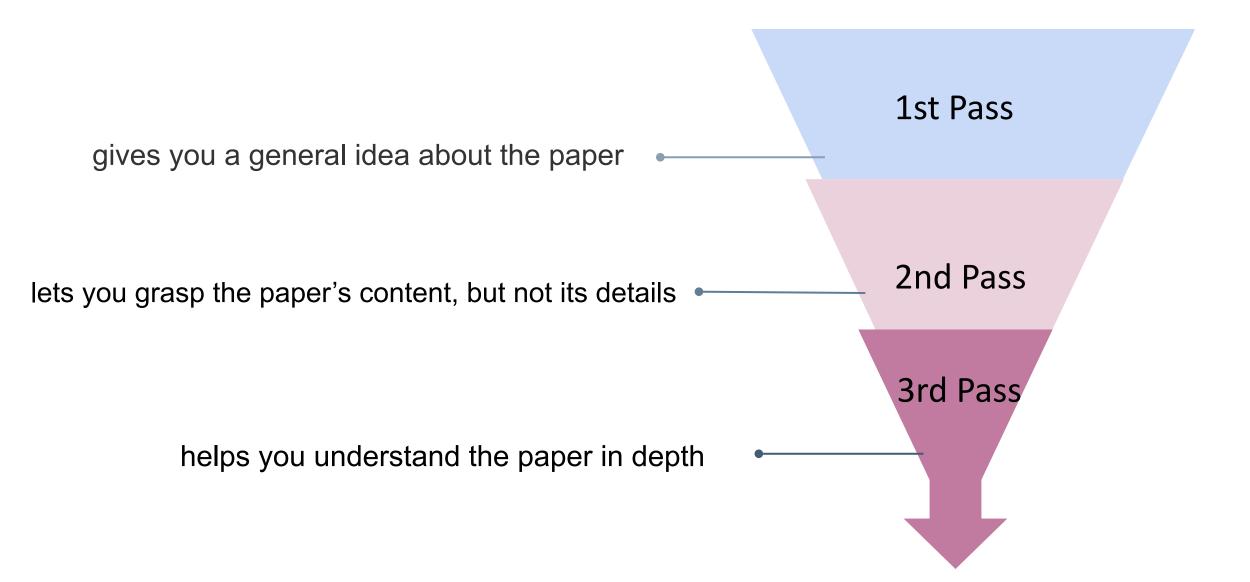
4. Glance over the references, mentally ticking off the ones you've already read

At the end of the first pass, you should be able to answer the *five Cs*:

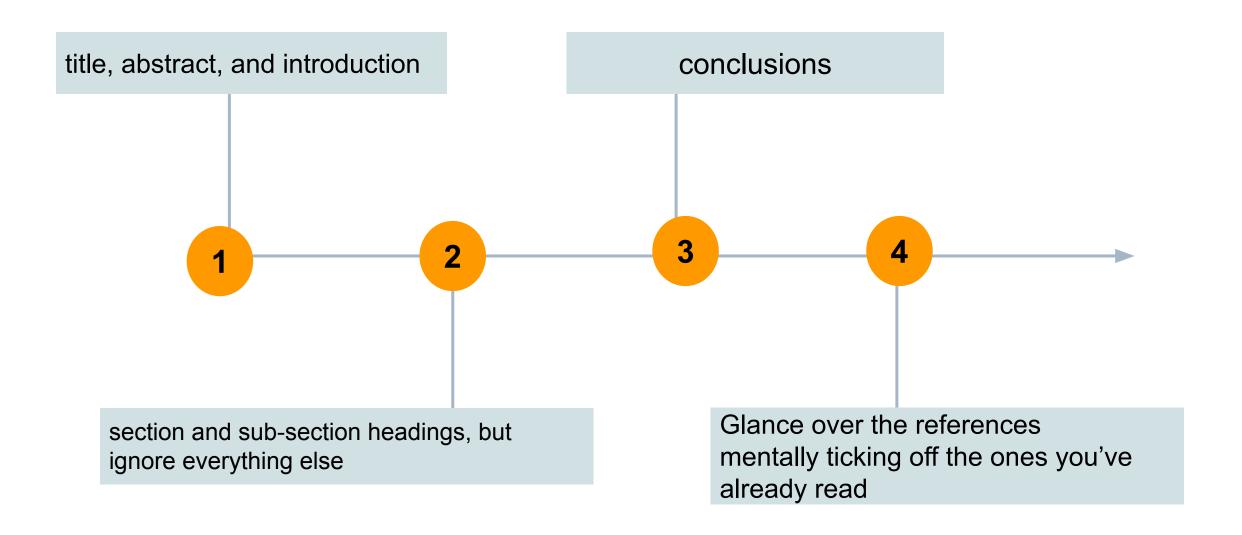
- 1. Category: What type of paper is this? A measurement paper? An analysis of an existing system? A description of a research prototype?
- 2. Context: Which other papers is it related to? Which theoretical bases were used to analyze the problem?
- 3. Correctness: Do the assumptions appear to be valid?
- 4. Contributions: What are the paper's main contributions?
- 5. Clarity: Is the paper well written?

Using this information, you may choose not to read further. This could be because the paper doesn't interest you, or you don't know enough about the area to understand the paper, or that the authors make invalid assumptions. The first pass is adequate for papers that aren't in your research area, but may someday prove relevant.

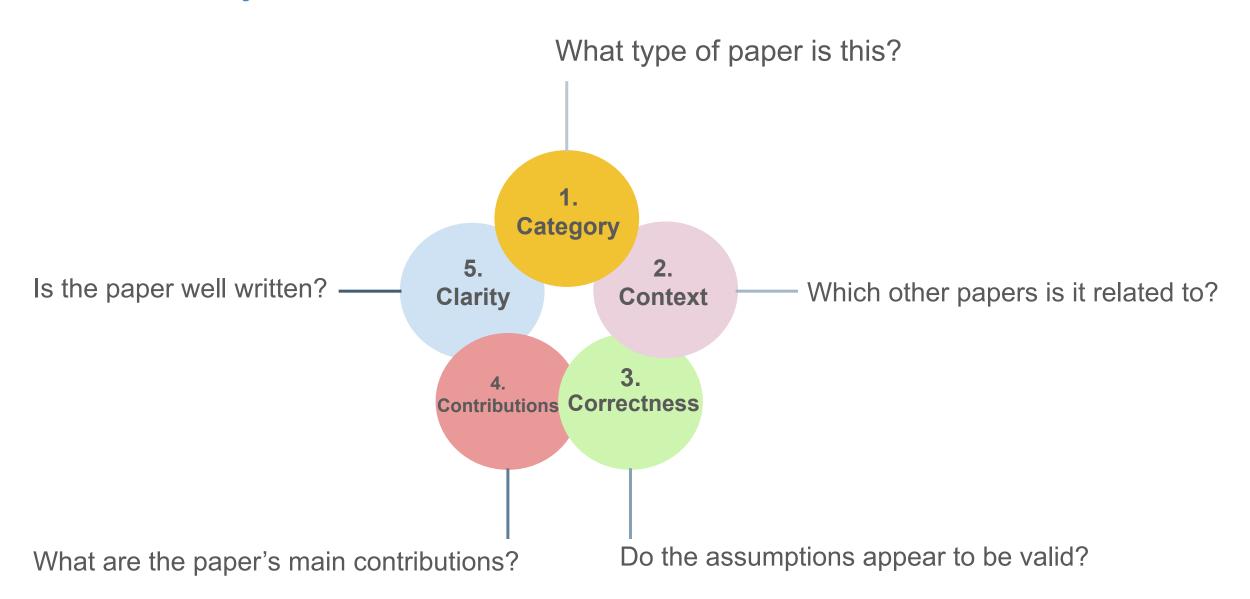
# The Three Pass Approach



### **First Pass**



### End of first pass: 5 Cs



# **First Pass Key Points**



You may choose not to read further



Most reviewers make **one** pass over papers



Enough for non research area papers



Choose **coherent** section and subsection titles and write comprehensive abstracts



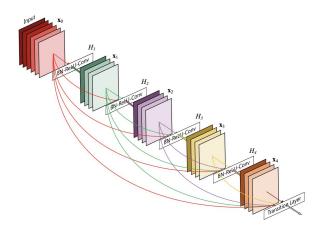


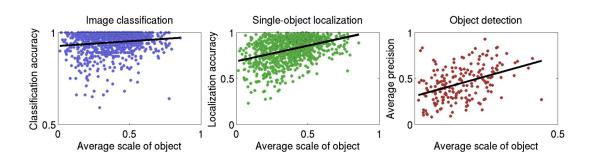
### **Second Pass**

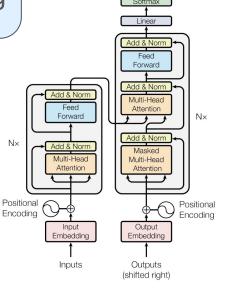
Read the paper with greater care, but ignore details such as proofs

1. Look carefully at the figures, diagrams and other illustrations in the paper.

2. Remember to mark relevant unread references for further reading

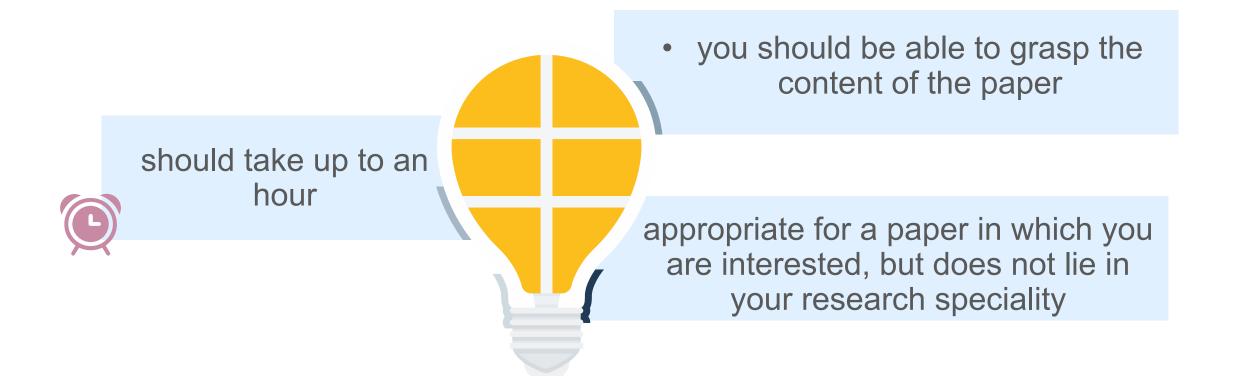






Output

# **Second Pass Key Points**



# **Second Pass Key Points**

If you don't understand paper:

Set the paper aside, hoping you don't need to understand the material

Return to the paper later, perhaps after reading background material

Persevere and go on to the third pass.

### **Third Pass**

- To fully understand a paper
- The key: attempt to virtually re-implement the paper
- Attention to the algorithms and pseudo codes
- Requires great attention to detail
- challenge every assumption

### Algorithm 1: ASA-GNN Approach

```
Input: TG \mathcal{G} = (\mathcal{V}, \mathcal{R}, \mathcal{P}, \mathcal{W}eight, \mathcal{E}),
               number of layers K,
               neighbourhood sample size \hat{z},
              Weight: \{w_1, ..., w_m\},\
               non-linear activation function \sigma.
    Output: embedding representation h_v^K of each node v
 1 h_v^0 \leftarrow r_v, \forall v \in \mathcal{V}; // Initialization
 2 for each layer k = 1, 2, \dots, K do
           for each i = 1, 2, \dots, \hat{z}_k do
                 // Neighbor sampling
                 \mathcal{N}_{v}^{i} \leftarrow select neighbors from \mathcal{N}_{v} according to Eq. (7);
                 if c_v = 1 then
                        over-sample neighbors according to Eq. (8);
 8
                 end
           end
9
           for each node v \in \mathcal{V} do
                 // Aggregation
                 \alpha_{v,v'}^k \leftarrow \text{Eq. (11)};
                 h_{\Lambda f}^k \leftarrow \text{Eq. (18)};
                 g_v^k \leftarrow \text{Eq. } (14);
                 h_v^k \leftarrow \text{Eq. (15)};
           h_v^k \leftarrow h_v^k / ||h_v^k||_2, \forall v \in \mathcal{V};
18 end
```

### **Third Pass**

you should think about how you yourself would present a particular idea



jot down ideas for future work

can take about four or five hours for beginners, and about an hour for an experienced reader

## Third pass checklist

- Be able to reconstruct the entire structure of the paper from memory
- Be able to identify its strong and weak points
- Be able to pinpoint implicit assumptions, missing citations to relevant work, and potential issues with experimental or analytical techniques.

# Summary

- Two strategies: extensive reading and intensive reading
- When and why and how to read Extensively/Intensively
- Intensive reading: Three pass approach

# Thanks!

