



MIDL
Winter Workshop

“How to write an award-winning paper”

or “how to be understood by your peers”

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Overview

Foreword

Before writing

Anatomy of a paper

Short break and first questions

Writing the paper

After writing

Summary and questions

Foreword

Why this workshop?

Papers are the main way to communicate ideas, to your peers.

Traditional publishing process

- Research & science: you
- Manuscript: you
- Typesetting: professional typesetter
- Printing: professional printer

Modern publishing process

- Research & science: you
- Manuscript: you
- Typesetting: you and **TEX**
- Printing: variable

Disclaimer and warnings

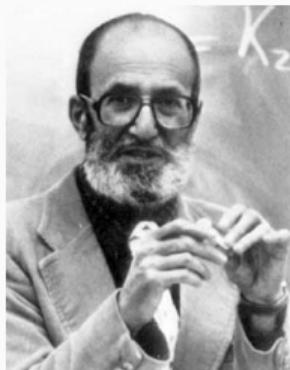
Keep in mind that:

- some papers & books are written over months or even years;
- there is always a deadline, do not burn yourself for one;
- rejection is part of the process.

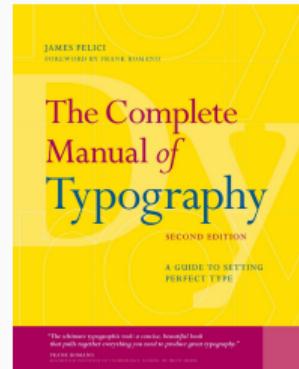
How I write papers, or actually *how I attempt to write papers*.

Find and refine your own method

Other readings



“How to write mathematics” — Paul Halmos,
1970



Paul Halmos said:

«The problem is to communicate an idea. To do so, and to do it clearly, you must have something to say, and you must have someone to say it to, you must organize what you want to say, and you must arrange it in the order you want it said in.»

Before writing

Scientific reading

Read papers, practice summarizing them

Review papers

How to write an outstanding review

You were invited to review for MIDL 2024, for another venue or even a journal? You want to take your first steps in writing reviews independently, or you just want to become more efficient in doing so? Join this workshop to learn how to write outstanding reviews. After a tutorial loaded with hints from experienced, senior colleagues, you will discuss real reviews from previous MIDL editions, including their rating by the program board. You will learn how to open up your own mind to grasp a manuscript from different perspectives, and how a review should be formulated to give a value to the authors. We are proud that the workshop will be led by Prof. Dr. Maria Vakalopoulou from CentraleSupélec. She will be supported by a great team, stay tuned.

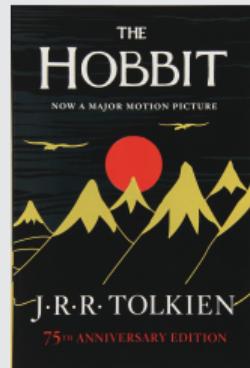


Improve your English

Actively: make a list of interesting formulations.

Passively: Read non-scientific books!

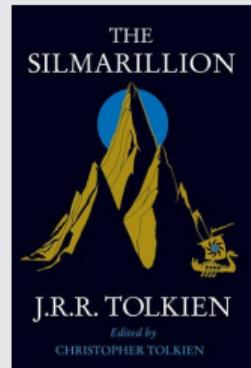
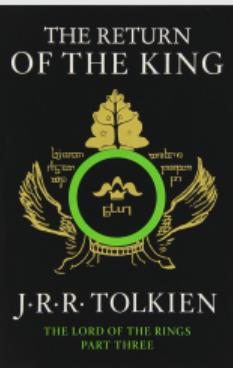
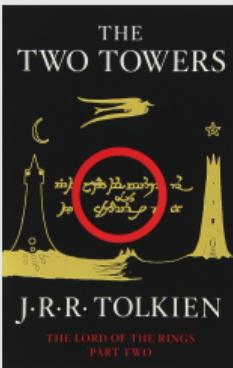
Personal favorites:



Beginner



Intermediate



Advanced

Master your tools

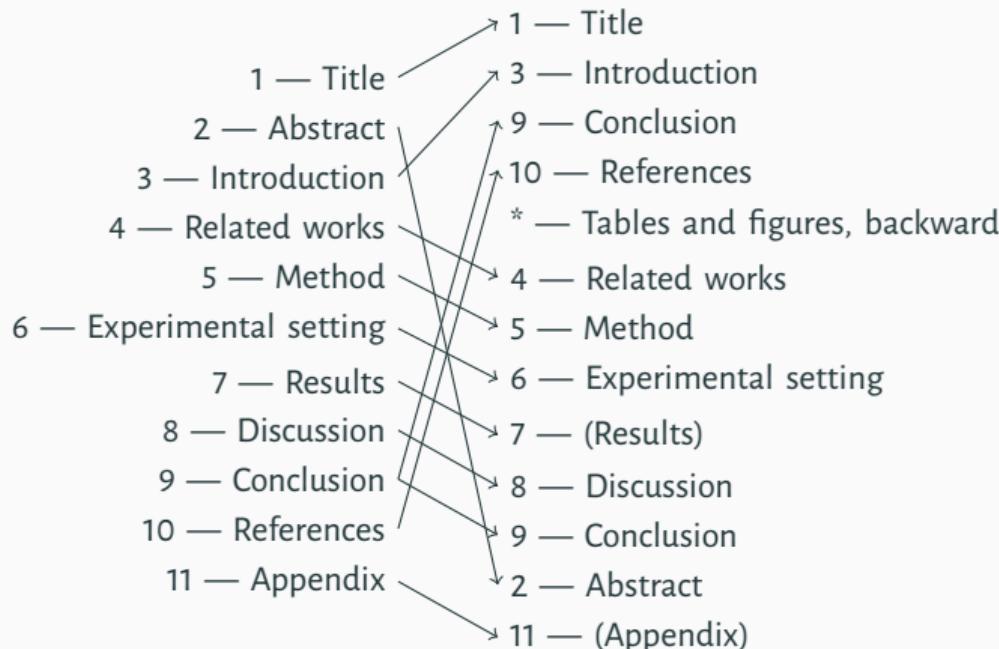
Make your life easier, can focus more on the writing.

Include:

- \LaTeX ;
- text editor;
- automate figures and plots;
- git;
- large screen;
- keyboard and touch-typing.

Anatomy of a paper

Paper structure and reading order



Similar structure for benchmark and surveys; though with a different emphasis.

The infinite ways to read a paper

A scientific paper is rarely read from front to back.

From a few minutes to a few hours.

People also come back at it after months or years.

⇒ Information should be easy to find

1 — Title

Short and informative.

How researcher notice your paper in a list.

2 – Abstract

Synthesis of the paper.

Discuss very quickly:

- topic and motivation;
- overall method (without details);
- main results.

3 — Introduction

What is the field, why is it of interest.

Which sub-problem do you want to tackle?

How the litterature is not sufficient to solve it.

Overview of your contribution: summary and teaser.

A good figure helps understanding and stoke interest

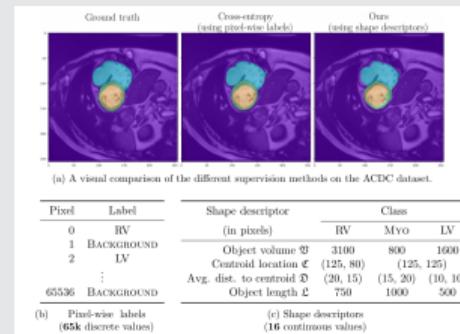


Figure 1: RV, Myo and LV stands for “right-ventricle”, “myocardium” and “left-ventricle”, respectively. The shape descriptors are detailed in Subsection 2.2.

4 — Related works

Why the existing literature is not sufficient.

Be **fair** to other researchers works.

Not simply a list: ground-work for your method.

Pseudo-writing:

A did X, and B did Y, but it is not fully applicable to P because of R. Z is the closest work but limited to tasks T.

5 — Method

Most important section: How does your method work?

Supported by:

- mathematical notation (**if relevant**);
- figures (could be Fig 1).

Some details can be left in the Appendix, or the public code.

Pseudo-writing:

We start from ZZ, which is the simplest and closest model. We build A and B on top of it, because RRR. Our final method is therefore ZZAB.

6 — Experimental setting

How are you going to evaluate your method?

Dataset, metrics, main hyperparameters, tools and frameworks.

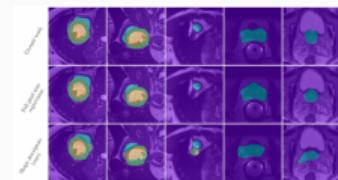
Methods you compare to (if relevant).

Pseudo-writing:

We use D dataset and evaluate with metrics M1 and M2. Code is implemented in F and is available online. We compare to A because it is relevant.

7 — Results

Both qualitative and quantitative results (if possible).



Method	ACDC			PROMISE12	
	RV	MYO	LV	Overall	Prostate
Cross-entropy (pixel-wise)	0.879 (0.066)	0.829 (0.074)	0.919 (0.059)	0.876 (0.076)	0.871 (0.047)
Ours (shape descriptors)	0.825 (0.107)	0.660 (0.114)	0.819 (0.086)	0.768 (0.128)	0.651 (0.098)

Pseudo-writing:

It works, by this much.

8 – Discussion

What is the consequence of your results?

New findings? New paradigm? Exciting new experiments to perform?

Current limitation? **Be honest.**

Pseudo-writing:

It works, therefore...

Yet, A, B and C remains.

9 — Conclusion

Summarize your findings:

- which problem did you solve;
- how did you solve it;
- by how much;
- opening: what remains?

10 — Bibliography

Done by \LaTeX .

Make sure journals are up to date.

Avoid duplicates.

11 – Appendix

Start on a \newpage: not a mandatory part of the paper.

Put the details **not needed to understand** the paper.

Short break and first questions

Writing the paper

Writing schedule example

First step: Figure out your best writing time slot.

- Start from paper template
- Write sparsely, just fill ideas there and there
- Placeholder for figures and tables
- Ask for first feedback: focus on the big picture and flow, not the details
- Continue filling sections, without priority: as the inspiration comes
- Start filling results, and see if there is a mismatch with the current writing
- Start refining from beginning to end. **Iterate**
- Near the deadline, compress the paper: remove redundant parts, make the sentences more to the point, tweak the figures placement

Refine a method **that works for you**.

Revisiting bounding boxes: weakly supervised image segmentation with inequality constraints and tightness prior

Anonomous Dupont

Editors: Under Review for MIDL 2020

Abstract

This is a great paper and it has a concise abstract.

Keywords: CNN,image segmentation,weak supervision,bounding-boxes

1. Introduction

Bounding boxes: uncertainty to deal with
Can reuse annotations made for object detection

2. Related works

Deep cut and Papandreou et al
Grab cut ?
That NIPS 2019
Orig 2009 from victor

3. Method

Put here a Figure with the labels used

3.1. On how to deal with the certainty outside the box

3.2. On how to deal with the uncertainty inside the box

3.3. Additional regularization: constraining the size

3.4. Constrained optimization with log-barrier

3.5. Final model

4. Experiments

4.1. Datasets

4.1.1. PROSTATE SEGMENTATION ON MR-T2

The third dataset was made available at the MICCAI 2012 prostate MR segmentation challenge¹. It contains the transversal T2-weighted MR images of 50 patients acquired at different centers with multiple MRI vendors and different scanning protocols. It is comprised of various diseases, i.e., benign and prostate cancers. The images resolution ranges from $15 \times 256 \times 256$ to $54 \times 512 \times 512$ voxels with a spacing ranging from $2 \times 0.27 \times 0.27$ to $4 \times 0.75 \times 0.75\text{mm}^3$. We employed 40 patients for training and 10 for validation.

¹ <https://promise12.grand-challenge.org>

4.1.2. ATLAS

Brain lesion, 100 patients

4.2. Implementation details

Fully residual Unet for PROMISE with BS 4, ENet for ATLAS with BS 32

Data aug for promise

Batch the box prior constraints by 5 ; this value didn't affect much the results

log-barrier params: defaults value from logbarrier paper

Balance of the weights can be found in the recipe in the code (prostate.make, atlas.make).

5. Results

Method	3D DSC
Deep cut	-
Box prior + box size	...
w/ negative cross-entropy	77.45
w/ empty background size	81.66
Full supervision (Cross-entropy)	90.09

Table 1: Table of the results for PROMISE12

Method	3D DSC	2D DSC	HD
Deep cut	-	-	-
Box prior + box size	-	-	-
w/ negative cross-entropy	-	-	-
w/ empty background size	-	-	-
Full supervision (Cross-entropy)	-	-	-

Table 2: Table of the results for ATLAS

5.1. Efficiency

On a machine with a Titan RTX:

Method	it/s (PROMISE)	it/s (ATLAS)
Base (cross-entropy)	9	5
w/ box prior (naive implementation)	7	-
w/ box prior (fast implementation)	8?	-
Deep cut	??	??

Table 3: Comparison in training speed between the different methods

Language

Write in plain English, use your own vocabulary.

Do not use short ways (“Don’t”, “Isn’t”, ...).

Remember: typographic conventions might be different from your native language.

If possible, ask for proof-reading from a native speaker.

Iterating: a few tricks to improve it

Ideal writing is spread over weeks, even months.

Some tips to accelerate it:

- Sleep!
- Exercise
- Any social activity bound in time
- Print the paper, draft with a pen
- Use a different pdf viewer/change the zoom settings
- Read it out loud

Explaining your method (i)

Paul Halmos said:

«The writer must anticipate and avoid the reader's difficulties. As he writes, he must keep trying to imagine what in the words being written may tend to mislead the reader, and what will set him right.»

Do not start with the final model, tell a story.

Be honest: how did you come up with your method?

Why did you do *this*, and not *that*?

Explaining your method (ii)

Paul Halmos said:

«Half of the art of good writing is the art of omission.»

Do not draw the reader with details. Reintroduce what is needed, without copying the full bibliography

Rule of thumb: how long did it take for you to notice it was required?

A picture is worth a thousand words.

Explaining your method (iii)

Do not try to sound smart.

The *reader* should feel smart.

Gently nudge him toward the next idea: make him “guess” it.

Explaining your method (iv)

Nicolas Boileau-Despréaux said:

« Whatever is well conceived is clearly said,
And the words to say it flow with ease. »

If you struggle to describe your idea, perhaps should go back on the drawing board.

Is your method as simple as it could be? Are you clear on what you are trying to achieve?

Do you have multiple goals and ideas that could be spread in several papers?

Mathematical notation (i)

Paul Halmos said:

«[One] other thing I would recommend that you do first is to invest an hour or two of thought in the alphabet ; you will find it saves many headaches later.»

Styles help:

$\$abcABC123\$$	<i>abcABC123</i>
$\$\\mathbf{abcABC123}\$$	abcABC123
$\$\\mathsf{abcABC123}\$$	<i>abcABC123</i>
$\$\\mathfrak{abcABC123}\$$	<i>abcΑΒC123</i>
$\$\\mathcal{ABC}\$$	<i>A<small>B</small>C</i>
$\$\\mathbb{ABC}\$$	A<small>B</small>C

Mathematical notation (ii)

Font styles can carry semantics.



Public code/data

Make it public if you can.

Can reference it in the manuscript, complement it.

<https://zenodo.org/> good option for archival and citation.

Asking for feedback

Ask regularly for feedback, from outsider.

What kind of feedback you need:

- overall sections structure;
- flow of ideas;
- formulation of the method;
- English and grammar;
- a specific Section?

Learn to **accept criticism**.

Build your network of proof-readers.

Giving feedback

Mention the good.

Be constructive: suggest improvements.

Mention if something is *difficult* to understand.

Writing helpers

Table of contents (with deep sectioning).

Show frame, helps to deal with figures placement.

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Table 2: Results of 1-way 1-shot and 1-way 5-shot segmentation on COCO-20 thing mIoU metric. Best result in bold.

Method	Backbone	1-shot					5-shot				
		Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	Mean
PSPNet [23] (FCN-20)	R50	34.5	35.5	24.5	18.0	35.7	40.3	30.9	35.7	30.2	36.2
FCN-20 [23]	R50	34.5	35.5	24.5	18.0	35.7	40.3	30.9	35.7	30.2	36.2
PSANet [30]	R50	33.3	36.8	34.3	33.8	36.5	43.7	37.8	38.4	36.3	38.7
TBHD-GD + SDF [16]	R50	31.8	36.3	36.1	34.3	35.2	40.5	45.4	40.9	40.7	41.8
TBHD-GD + SDF (ours)	R50	31.8	36.3	36.1	34.3	35.2	40.5	45.4	40.9	40.7	41.8

* We report the results where no additional baseline is required.

Table 3: Aggregated results for 1-way 1-, 5- and 10-shot tasks with MS-COCO as backbone and averaged over 4 folds. The best results are available in the appendix, Table 8.

Method	PASCAL-3D			COCO-20		
	1-shot	5-shot	10-shot	1-shot	5-shot	10-shot
RPN [10]	40.5	56.9	55.0	5.9	5.8	5.7
FCN-20 [23]	40.5	56.9	55.0	5.9	5.8	5.7
PSANet [30]	40.5	56.9	55.0	5.9	5.8	5.7
TBHD-GD + SDF [16]	40.5	56.9	55.0	5.9	5.8	5.7
TBHD-GD + Oracle (ours)	40.5	56.9	55.0	5.9	5.8	5.7

ations to the data collection process might result in a distributional shift. We reproduce the scenario where n large labeled datasets is available (i.e., COCO-20), but the test set is drawn from a different distribution with different feature distribution (e.g., PASCAL-3D). As per the original work [15], significant differences exist between the two datasets. For example, COCO-20 has MS-COCO has on average 1.7 times more of objects ranging from 2-5 distinct categories, while PASCAL-3D only has an average of 3 instances from 2-5 distinct categories.

4.3. Ablation studies

In this section we perform several ablation studies to evaluate the influence of important components of our model on the segmentation performance.

Impact of each term in the main equation. While Fig. 1 provides qualitative insights on how each term in Eq. (1) affects the final prediction, this section provides a quantitative evaluation of their impact, resulting in Table 4. The first row shows the results when the CE + $N \cdot D_{CE}$. For example, in the 1-shot scenario, simply removing the CE results in more than 20% drop in mIoU. This indicates that the cross-entropy loss, the prototype or trade-off to credit the support sample and only activates regions of the query object that are present in the support sample, are all important. However, replacing the prototypes when the support and query objects exhibit slight changes in shape or orientation, such as in the 5-shot setting, the CE loss becomes less important. In addition, the $N \cdot D_{CE}$ term partially alleviates this problem, as it tends to refine the model by forcing it to predict positive pixels. Nonetheless, despite improving the naive CE based model, the gap with the proposed model remains considerably

Evaluation. We reuse models trained on each fold of COCO-20 thing and using linear fusion of all the folds for the PASCAL-3D task to evaluate the proposed training. For instance, fold-0 fit this setting since the model was trained on 5440 of COCO-20 and tested on the remaining 4559 images. We report the results of the used strong training. A complete summary of all the folds is available in the Supplemental material.

Results. We reproduced and compared to the most popular methods [23, 21] using their respective official GitHub repositories. Table 4 summarizes the results for the 1-shot and 5-shot dataset experiments.

As shown in Table 4, our proposed method outperforms existing methods in both 1-shot and 5-shot scenarios.

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Table 4: Ablation study on the effect of each term in our loss in Eq. (1), evaluated on PASCAL-3D.

Loss	1-shot				5-shot				Mean	
	Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	
CE	45.7	61.7	49.2	38.4	48.8	56.8	60.3	47.0	58.4	50.0
CE + $N \cdot D_{CE}$	40.9	68.3	62.1	48.5	50.7	64.6	71.4	71.3	58.6	60.0

large, with 10% difference. On the other hand, the differences between CE and $C + N \cdot D_{CE}$ decrease in the 5-shot setting, since overlapping 5 support samples simultaneously becomes more difficult. The results from this ablation study confirm our initial hypothesis that the proposed loss term based on the size prior acts as a strong regularizer.

Impact of prior information. Finally knowing the foreground/background (FB) proportion of the query object is crucial. To quantify the deviation from the exact FB proportion w^* , we introduce the relative error on the foreground class:

$$\delta^F = \frac{|\hat{w}^F - w^*|}{w^*} - 1 \quad (6)$$

where \hat{w}^F represents the exact foreground proportion in the query image, extracted from its corresponding ground truth, and w^* is our estimate at iteration 0, which is derived from the soft predicted segmentation. As shown in Table 5, the proposed loss is able to derive a sharp probability map, from which only a very coarse estimate of the query proportion can be inferred and used for training. The difference between the values presented in Table 5 clearly shows that the initial prediction typically provides no estimation of the actual query foreground size, while thinning the distribution of the prototypes to the support sample in Eq. (1) provides a much more accurate estimate, as confirmed by the right box plot in Fig. 2b, with an average error of 0.01.

Now, a natural question remains: how good are the estimates needed to be in order to approach the oracle performance? To answer this question, we conducted experiments where instead of computing \hat{w}^F with Eq. (3), we use a δ -perturbed oracle of initialization, such that $\hat{w}^F = w^* + \delta$. The results are shown in Table 6. In the 1-shot setting, our model consistently outperforms the oracle when δ is large enough. For the 5-shot setting, the oracle provides a much better estimate of the query proportions, which is reflected in the smaller gap between the differences in scores across the folds. Furthermore, in our setting $C = 512$, and therefore the problem cannot be solved with a single prototype vector. In this case, the oracle performs significantly worse than the proposed method. This is due to the fact that the oracle is not able to learn a good prototype vector, as the prototypes are not well separated. The proposed method, however, is able to learn a good prototype vector, as the prototypes are well separated. The proposed method also outperforms the oracle when δ is small, with a gap between the oracle and the proposed method decreasing from ~10% to ~3%. This is due to the fact that the oracle is not able to learn a good prototype vector, as the prototypes are not well separated. The proposed method, however, is able to learn a good prototype vector, as the prototypes are well separated.

Computational efficiency. We now inspect the computational cost of the proposed model, and compare to related methods. Unlike prior work, we selected the backbone R50 as the base model, as it is the most commonly used backbone in the field. The proposed model takes ~1.5 seconds to run on a single GPU. This is ~1.5 times slower than the state-of-the-art [16]. The difference in inference time is mainly due to the prior estimation. Both figures are computed using 5 runs of 1000-10k shots tasks on the GPU of a 5400-MP3A.

Figure 2: Experiments on prior estimation. Both figures are computed using 5 runs of 1000-10k shots tasks on the GPU of a 5400-MP3A.

which represents an improvement of 10% over the state-of-the-art. The suggests that using the proposed prior estimation methods may significantly increase the performance of the proposed method.

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Now, a natural question remains: how good are the estimates needed to be in order to approach the oracle performance?

Miscellaneous

Indent your code.

Commit often, keep your .tex clean.

Do not modify a sentence, rewrite it from scratch.

After writing

Clean-up, archival

Clean-up your code, remove comments, fix indentation.

Archive the:

- latex code;
- results and training artifacts.

Get ready...

Rebuttal or revision are coming:

- new metrics to compute;
- new experiments to run;
- merging results from different runs.

Summary and questions

Carl Friedrich Gauss said:

«I write slowly. This is chiefly because I am never satisfied until I have said as much as possible in a few words, and writing briefly takes far more time than writing at length.»

Summary

Main ingredient is time

Find a way to make writing fun, *for you*

Start early...

... and iterate

and again.