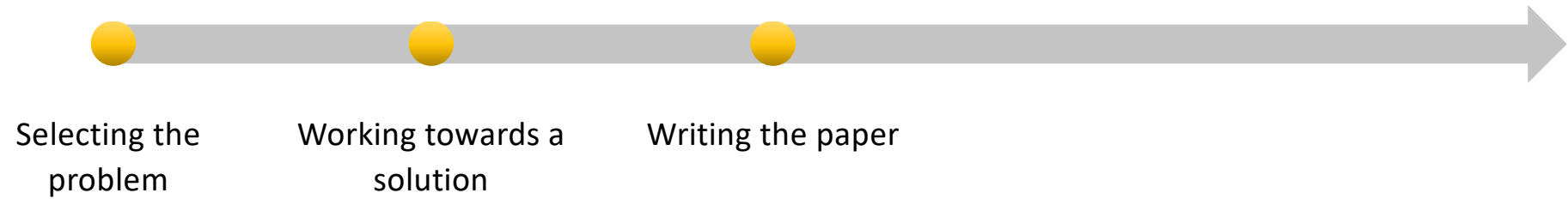


# From Ideas to A\* Papers: A Behind-the-Scenes Journey not Often Discussed

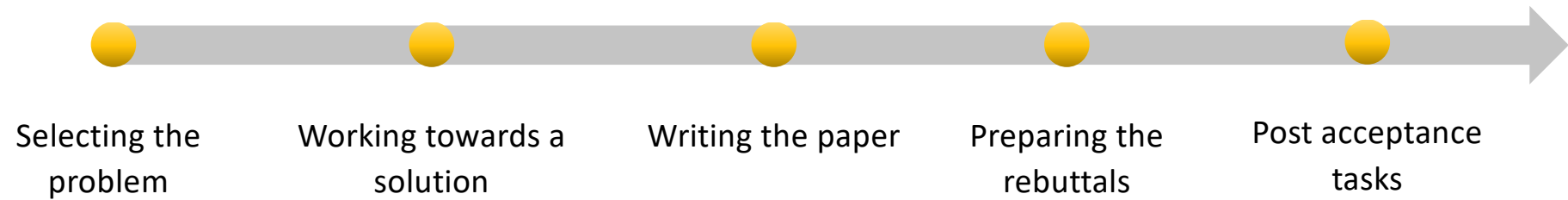
Joseph K J

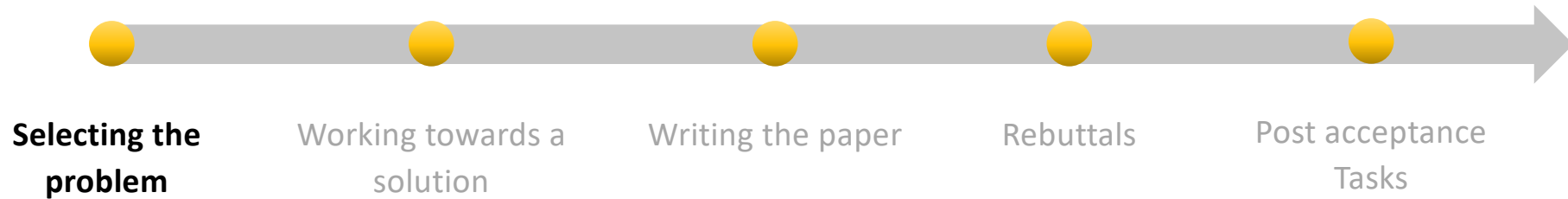
 **Observations might be biased towards Computer Vision and Machine Learning conferences.**

# Milestones

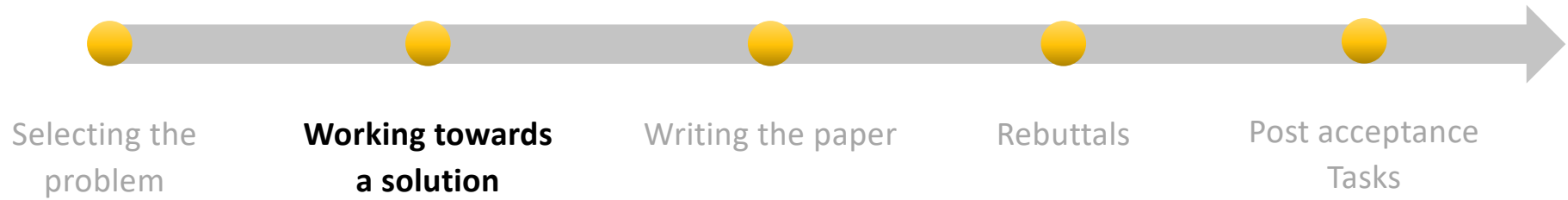


# Milestones





- Do something that you are really passionate about.
  - It's a roller-coaster, and your passion is your seat-belt
- Own the problem
  - It is your PhD thesis
- Practical tips
  - Select a topic that is not saturated.
  - Is of interest to the venues that you are targeting.
  - Even early on, shoot for the best venues.
  - Find the baseline paper that you are going to build on, ensure that the code is available.



- Setup your baseline.
- Iterate between coding and reading papers.
- Be organized with your code: use GitHub.

github.com/JosephKJ/OWOD/commits/master/?before=23890f188cd1a6801c6ac0e3dacd78b8572b8c29+70

Open in app

Paused

New Chrome available

master

All users

All time

Commits on Nov 12, 2020

- iOD

JosephKJ committed on Nov 12, 2020

68da418

<>

Commits on Nov 9, 2020

- Saving feature store

JosephKJ committed on Nov 9, 2020

81516e5

<>

Commits on Nov 6, 2020

Weibull distribution: Inference added

JosephKJ committed on Nov 6, 2020

ea9f7d1

<>

Weibull distribution

JosephKJ committed on Nov 6, 2020

71480aa

<>

Commits on Nov 4, 2020

Updated the evaluation display. Ready for t1\_std\_frcnn.

JosephKJ committed on Nov 4, 2020

9321996

<>

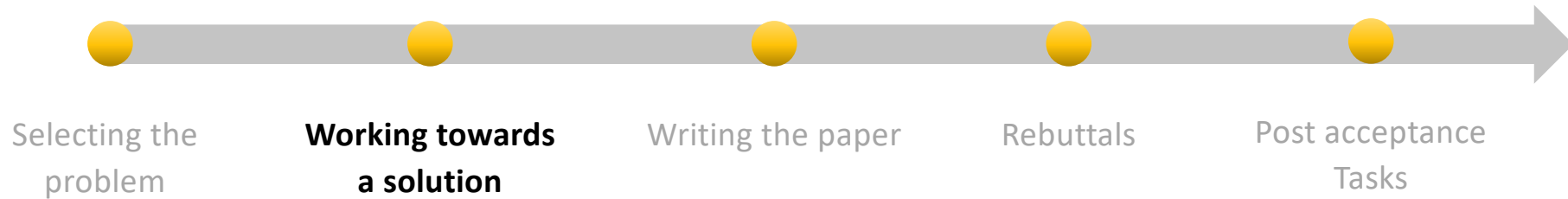
- Adding new imagesets

JosephKJ committed on Nov 4, 2020

92312cc

<>

Commits on Nov 3, 2020



- Setup your baseline.
- Iterate between coding and reading papers.
- Be organized with your code: use GitHub.
- Stuck? First, talk to yourself.
  - Maybe a white-board
  - Write things down
  - Then discuss with others  
(don't expect anything from anyone, if you get, be grateful)
- Be organized with your work: log it.
  - Be prepared to be disturbed.



	A	B	C	D	E	F
248	1) Mar 15 - Mar 21					
249	Papers					
250	1	Continual Unsupervised Representation Learning	NeurIPS 19	Introducing "Unsupervised Continual Learning": --- Task label and boundary is unknown. (Task aware setting) --- Each datapoint is not assigned label (Un-supervised Learning) A mixture of gaussian is assumed where each component is specific to each task. Each component is dynamically added. An extension to Variational Deep Embedding.	MNIST Omniglot	
251						
252						
253						
254						
255						
256	2	Unsupervised Continual learning and Self-Taught Associative Memory Heirarchies	LLD Workshop	They introduce a new STAM architecture that rivals CNN.		Problem definition is similar
257			ICLR 2019	Slight few-shot flavour to the problem, as during inference, few labelled examples are used.		
258						
259	3	Automatically discovering and learning new visual categories with ranking statistics	ICLR 2020	Primarily focused on (un)supervised clustering of novel classes; a set of labelled base class images are available. Use RotNet to get a feature representation which is finetuned. Pseudo Labels are generated for the novel class images.		
260						
261						
262						
263						
264	Summary of main points discussed in the meeting (Salman)					
265	[17 Mar 20]	▸ Incremental Few-shot: See how we compare against the CVPR 2020 paper.				
266		▸ Extending the ECCV Submission				
267		→ CenterNet, RetinaNet				



Updates ▾

Manuscript ▾

Timeline ▾

Reporducing results ▾

Supplementary Section ▾

Items for clustering ▾

Momentum ▾

Margin ▾

1 Data



	A	B	C	D	E	F	G	H
1	Idea 1	Auto-label unknowns and learn						
2		Self attentive maps						
3								
4	Idea 2	BNN instead of classifier and regressor						
5		- Uncertainly modelling.						
6								
7	Idea 3	Expore Outlier detection methodoloies						
8								
9								
10	Idea 4	Inspiration from Active Learning?						
11								
12								
13	Idea 5	Would edge detection help for unknown detection as its class agnostic?	<a href="https://arxiv.org/pdf/1902.10903.pdf">https://arxiv.org/pdf/1902.10903.pdf</a>					
14								
15								
16	Idea 6	There are these papers which says that finetuning with exemplar set is all that is required.						
17		- GDumb, ECCV 2020	<a href="https://www.ecva.net/papers/eccv_2020/papers_ECCV/papers/123470511.pdf">https://www.ecva.net/papers/eccv_2020/papers_ECCV/papers/123470511.pdf</a>					
18		- Frustratingly Simple Few-Shot Object Detection, ICML 2020	<a href="https://proceedings.icml.cc/static/paper_files/icml/2020/2957-Paper.pdf">https://proceedings.icml.cc/static/paper_files/icml/2020/2957-Paper.pdf</a>					
19		Hence, why dont we just finetune to prevent Catastrophic forgetting with a small subset of data. How we select the data would be important then.						
20								
21								
22								
23								
24								



2 Methodologies ▾

2 Methodology-v1 ▾

1 Methodology-v2 ▾

Wilderness Results ▾

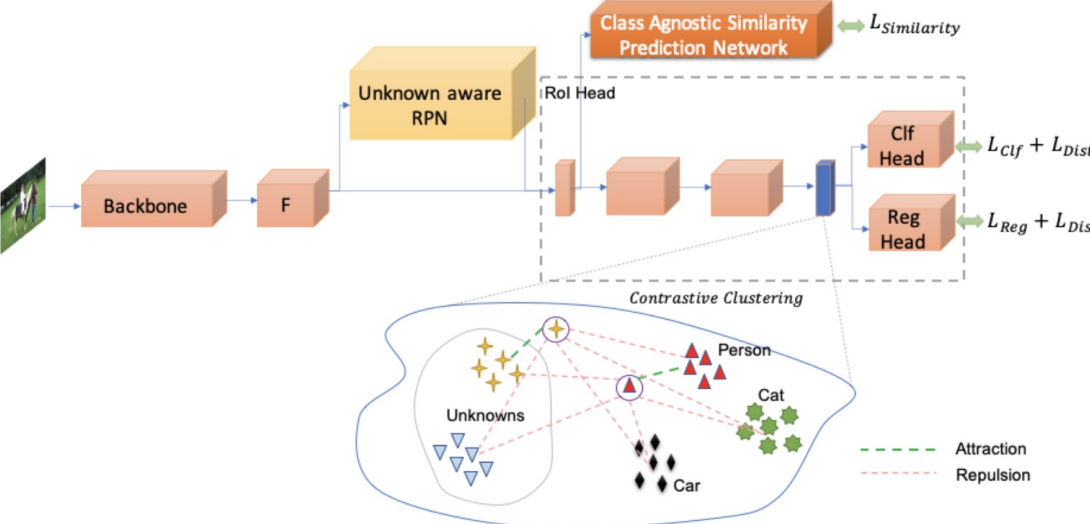
Evaluation Metric ▾

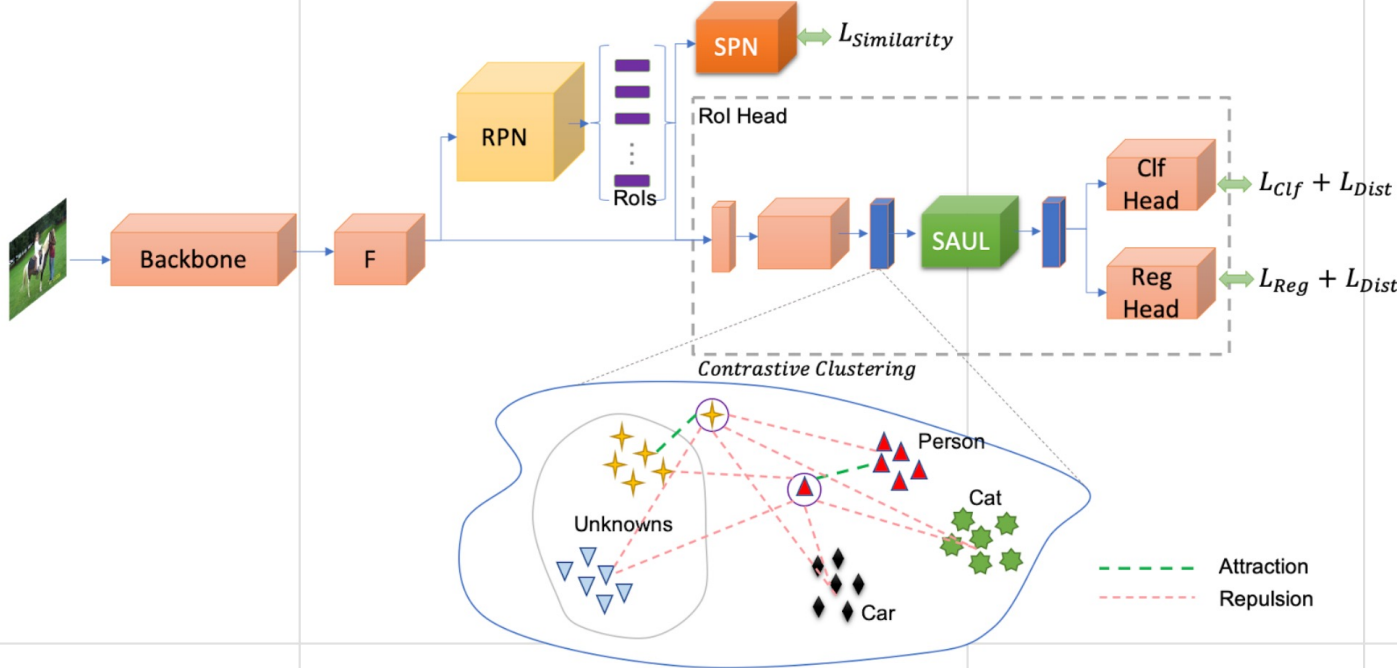
TODO ▾

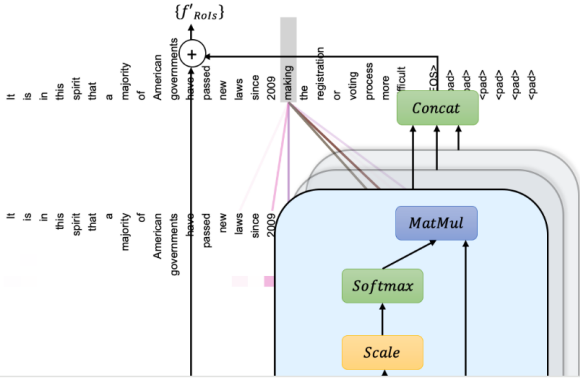
(old) Results ▾

(old) Quant



	A	B	C	D	E
1	Highlevel phases: Image -> Backbone -> Unknown Aware RPN -> Similarity Prediction Network -> Contrastive Clustering -> MixDist				
2					
3	(NB: All citations refer to the papers in the first sheet.)				
4	Component	Methodology	Positives	Negatives	Additional ways to improve
5	Unknown Aware RPN	Label top-k (based on objectness score) background proposals as Unknown.	Easy way to auto-label an unknown. Qualitative results are coherent.	- Hyper-parameter k, i, o	1. Some boundary detection loss to improve the objectness score. 2. Better Uncertainty estimation methodology (similar to the latent exploration method)
6		Background proposals are those with IoU < i		- Seems to be a simple hack.	
7					
8					

	A	B	C	D	E
1	Highlevel phases (v1): Image -> Backbone -> Unknown Aware RPN -> Similarity Prediction Network -> Contrastive Clustering -> MixDist				
2	Highlevel phases (v2): Image -> Backbone -> RPN -> Similarity Prediction Network -> Contrastive Clustering -> Self Attentive Unknown Labeller -> MixDist Exemplar replay + Distillation				
3					
4					
5	Component	Methodology	Discussion	Positives	Negatives
6	RPN	The standard RPN, which produces region proposals (objectness score and BB offsets).			
7		It is class specific			

	A	B	C	D	E
11					
12		<p>Intuition is that the unknown object will be attended to by the known objects. To be more explicit, we can assume that some of the background region proposals would be attended more (measured in terms of the number of in-bound attention links (hyperparam in_link)). Such background proposals can be labelled as unknown.</p>	<div><div>V</div><div>Vineeth N Balasubramanian 25 Sept 2020</div><p>What is the logic for this? Do we mean that these are more likely to mislead object detectors as being objects, than a more amorphous background?</p></div>		hyperparam: in_link
13		<p>Architecture of SAUL:</p> 	<div><div></div><div>Deleted user 25 Sept 2020</div><p>Yes, and even more importantly, such unknown object might be automatically discovered.</p><p>Comments above copied from original document</p></div>		

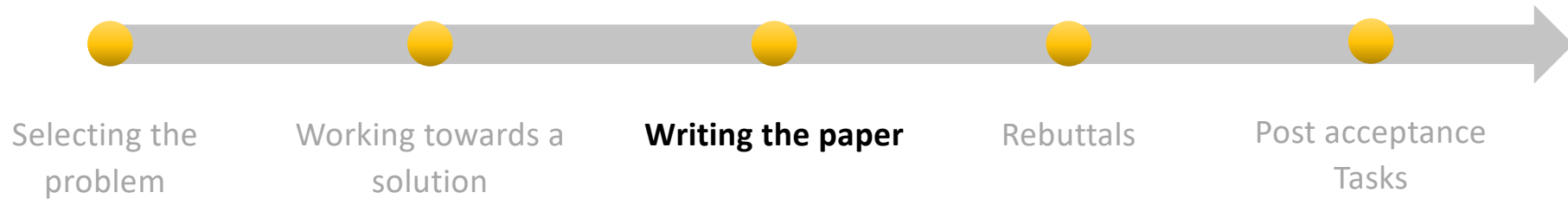


- Plan your writing: have a skeleton first.

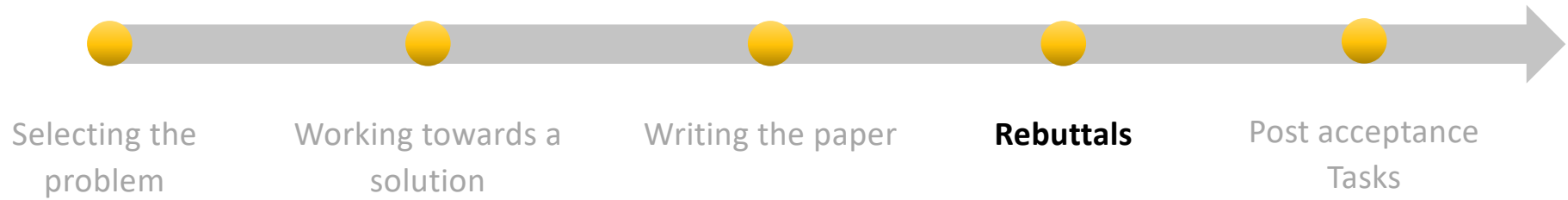
	B	C	D	E	F	G	H	I
13	Open World Object Detection							
14	Related Work	Methodology			Experiments and results			Conclusion
15		Problem Formulation	Proposed Solution	Evaluation protocol	Implementation details	Main Results	Additional results	
16			- Contrastive clustering	- Data split	8 Tesla V100 GPUs	- Ability to reduce the confusion of an unknown being labelled as a known.	- Main Ablations	
17			- RPN Thresholding based auto-labelling	- Evaluation metrics	Batch size: 8; one image per GPU	- Ability to explicitly identify an unknown	- Time taken: training and inference	
18			- Energy based unknown identification		Custom dataloader which labels images according to whether it is known or unknown	- Incremental OD results	- Plot of clustering loss.	
19			- Balanced finetuning for addressing catastrophic forgetting. (Mitigating forgetting)		While training $T_i$ , only classes in $T_i$ are labelled, all the others are ignored.		- TSNE of latent space	
20					How the extra class of backgrounds are added		- Qualitative results	
21			- A unified solution to OWOD, which is a symphony of		Handling incremental class growth.		- Memory Size	
22							- Confusion matrix?	
23	Open world dEtector						- Contribution of mixed unknown errors to the whole error.	
24							- Modelling the uncertainty: weibull distribution.	
25								
26								
27	ons							

	B	C	D	E	F	G	H	I	J	K	L	
23	Method					Scorer: Measuring Slide's Quality						
24	<input checked="" type="checkbox"/>		Why RL to improve slide generation?									
25	<input checked="" type="checkbox"/>			- Dataset for SFT is impractical to collect.								
26	<input checked="" type="checkbox"/>		How to adapt RL with noisy / imperfect rewards									
27	<input type="checkbox"/>											
28	<input type="checkbox"/>	Coactive Learning a Slide Stylizer										
29	<input checked="" type="checkbox"/>		Preliminary									
30	<input checked="" type="checkbox"/>			Takeaway: in expectation, if we have an improved version of the slide, it will help.								
31	<input type="checkbox"/>			We should introduce $\pi^*$								
32	<input type="checkbox"/>		Slide Stylizer									
33	<input type="checkbox"/>			We plan to learn a <b>single module comprising of planner and a coder</b> that can take in components, current rendition and generate a stylized								
34	<input checked="" type="checkbox"/>			<del>This single module is what we learn with coactive learning.</del>								
35	<input checked="" type="checkbox"/>			Creating $\pi^*$ similar to Tucker et al. needs human annotated data, but this is infeasible for us. Instead, we propose a way to sample and strictly								
36	<input checked="" type="checkbox"/>		Building a robust $\pi^*$									
37	<input type="checkbox"/>			How to generate improved feedback ( $\pi^*$ )?								
38	<input checked="" type="checkbox"/>			Qwen-VL - ZS								
39	<input checked="" type="checkbox"/>			Qwen-VL - FT or These models are trained only to make slight improvement, which greatly simplifies that ta								
40	<input type="checkbox"/>			How do we measure improvement?								
41	<input type="checkbox"/>			The scorer								
42	<input type="checkbox"/>			Show that it is good.								
43	<input checked="" type="checkbox"/>		Building single module comprising of planner and a coder									
44	<input checked="" type="checkbox"/>			Data generation pipeline								
45	<input checked="" type="checkbox"/>			SFT								
46	<input type="checkbox"/>			DPO								





- Plan your writing: have a skeleton first.
- First draw the figures and write any algorithms (if you may have).
- Certain parts of the paper can start early
  - Related works: during your initial literature review phase
  - Intro: have pointers early on.
- Plan to finish at-least one week before the deadline.
  - Iterate through it, to make it perfect.

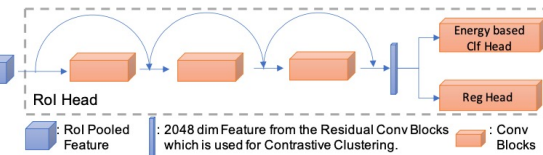


- Yes, it is possible to turn-around the papers with a clear rebuttal

We thank the reviewers for the positive feedback: *novel approach and problem setting (R1, R3), core ideas are interesting and worth explored (R2), addressed problem is very hard and very important for AI (R2), well-written (R1, R2, R3), literature survey is up to date and clearly explained (R1, R3), evaluation is well conducted (R2), extensive experiments and ablations to showcase different aspects (R3)*. Our source code and models will be publicly released.

**Reviewer 1 (R1) Name (OREO):** Thanks. We will rename our method. **Relation with embedding learning (EL):** Different from EL works, our approach performs clustering by using contrastive constraints on *dynamic prototypes from each class* (Eq 1) instead of single class instances. This is important for our OWOD problem since same class instances are desired to be mapped together while they must be far from *all other class instances* simultaneously. To our knowledge, we are the first to introduce a multi-way class-level contrastive formulation for the challenging OWOD problem. Further, contrastive constraints in most existing EL methods (*e.g.*, He *et al.*, MoCo, CVPR'20) have higher complexity and longer training times due to instance level

Figure A1. RoI head architecture, showing 2048-dim feature vector used for contrastive clustering. Best view zoomed in.



fold: 1) it enables the model to cluster unknowns separately from known instances, thus boosting unknown identification; 2) it ensures instances of each class are well-separated from other classes, alleviating the forgetting issue (L266). The 2048-dim feature vector that comes out from residual blocks of RoI head (Fig A1) is contrastively clustered (L592). The contrastive loss is added to the Faster R-CNN loss and the entire network is trained end-to-end (L371). We will clarify in revision. **Role of Energy:** The intrinsic capability of EBMs [23] to assign low energy values to in-distribution data and vice-versa motivates us to use an energy measure to characterize whether a sample is from an unknown class. **Clarification regarding Unknown Identification:** An unknown is *not identified by thresholding* in our case, but by computing the likelihood of the data point w.r.t a learned Weibull distribution, which is fit only once at inference and takes just 1.78 sec. **Comparison with**

COCO) as unknown, we need to re-annotate all images, which is laborious, as it takes  $\sim 20k$  worker hours just for point annotation on COCO [27]. Auto-labeling region proposals with our method is an effort to address this problem (Sec 4.2), but is not a substitute for ground-truth since pseudo labels are noisy. However, we show that our method can use these noisy pseudo labels to aid latent space separation via contrastive clustering, which helps better classification by the energy-based unknown identifier. **On Keeping all Data:** The storage and compute expense will grow unbounded if we are to store all data and retrain a model from scratch each time. We follow standard incremental learning settings [1,4,5,20,21,24,32,43,44,52,57] in this regard, which work without storing all data. We will clarify this in revision. **Difference from Open Set/World:** Fig 1 shows how our OWOD problem differs to Open Set/World.

We would like to borrow R2’s comment that OWOD setting is ‘very

hard and very important for AI’.

**Additional Baseline:** As suggested, we compare our method with [2, 3] in Tab A1 and will include these results in the revision.

**Reviewer 2 (R2) More Details on Contrastive Clustering:** The motivation for using contrastive clustering is two-

Method	WI ( $\downarrow$ )	A-OSE ( $\downarrow$ )	mAP-KU ( $\uparrow$ )	mAP-K ( $\uparrow$ )
Objectness[2]	0.089	14892	12.15	27.42
Deepbox[3]	0.069	13396	34.18	53.23
OWOD	<b>0.022</b>	<b>8234</b>	<b>56.34</b>	<b>81.31</b>

Table A1. Baseline comparison with [2, 3]. mAP-K: Only Known. mAP-KU: mAP on Known & Unknown. Best view zoomed in.

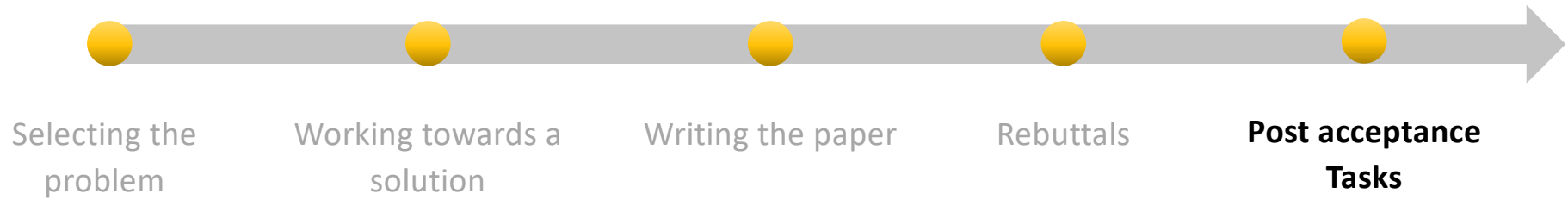
**Feature Compatibility:** Our balanced clustering helps improve feature compatibility. Thank you for sharing the idea of fixing the classifier. We will explore this promising direction as a next step and cite Shen *et al.*, Pernici *et al.*

**Reviewer 3 (R3) Failure Cases:** Occlusions and crowding of objects are cases where our method tends to get confused (*storage*, *walkman* and *bag* not detected as *unknown* in Figs. S5, S7). Difficult viewpoints (such as back-side) also lead to some misclassifications (*giraffe*  $\rightarrow$  *horse* in Figs. 4, S6). We have also noticed that detecting small *unknown* objects co-occurring with larger known objects is hard. We thank R3 and will include detailed failure analysis in revision. **Recall Threshold:** A high recall (0.8) was set to evaluate in a challenging scenario. At 0.5, we observe a slight gain in WI to 0.019. The change is not drastic since WI computation involves ratio of the precisions at a given recall. **Temperature:**

We fixed  $T=1$  (L121 in Suppl.). Softening the energies a bit more ( $T=2$ ) gives slight improvement in unknown detection (A-OSE and WI), however

increasing it further hurts as evident from adjacent table. **Energy Motivation:** Kindly see R2 (Role of Energy). **Other Issues:** We thank R3 and will cite and discuss recent detectors. Supplementary will also be referred adequately.

T	WI( $\downarrow$ )	A-OSE( $\downarrow$ )	mAP( $\uparrow$ )
1	0.0219	8234	<b>56.34</b>
2	<b>0.0214</b>	<b>8057</b>	55.68
3	0.0411	11266	55.51
5	0.0836	12063	56.25
10	0.0835	12064	56.31



- Make a webpage, YouTube video etc.
- Made your code and models public.

github.com/JosephKJ/OWOD

Open in app

Paused

New Chrome available

JosephKJ / OWOD

Type to search

Code

Issues30

Pull requests

Discussions

Actions

Projects

Wiki

Security12

Insights

Settings

OWODPublic

Unpin

Unwatch22

Fork154

Star1.1k

master2 Branches0 Tags

Go to file

Add file

Code

JosephKJ Update README.md23890f1 · 4 years ago77 Commits

configs	Updating paths.	5 years ago
datasets	Updating the finetuning image_list, the earlier version wa...	5 years ago
demo	Detectron2	6 years ago
detectron2	Updating the finetuning image_list, the earlier version wa...	5 years ago
dev	Detectron2	6 years ago
docker	Detectron2	6 years ago
docs	Add files via upload	5 years ago
projects	Detectron2	6 years ago
tests	Detectron2	6 years ago
tools	Auxillary changes (CVPR-21 submit tip)	6 years ago
GETTING_STARTED.md	Detectron2	6 years ago
INSTALL.md	Detectron2	6 years ago

About

(CVPR 2021 Oral) Open World Object Detection

josephkj.in

open-worldobject-detectioncvpr

incremental-learningenergy-based-model

continual-learningdetectron2

contrastive-learningcvpr2021

Readme

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Activity

1.1k stars

22 watching

154 forks

Contributors2

JosephKJJoseph K J

salman-h-khanSalman Khan

TITLE	CITED BY	YEAR
<b>Towards open world object detection</b> KJ Joseph, S Khan, FS Khan, VN Balasubramanian Proceedings of the IEEE/CVF conference on computer vision and pattern ...	789	2021







# Same START\_ITER values in t\*\_train.yam and t\*\_ft.yaml #40

Edit

New issue

✓ Closed



mmaaz60 opened on May 15, 2021

...

Hi,

I noticed that the value of `START_ITER` is the same in all corresponding `train` and `ft` configs. For example, it is `START_ITER: 18000` in both `t2_train.yaml` and `t2_ft.yaml`. As per the script [run.sh](#), the finetuning ( `t*_ft.yaml` ) is using the weights generated from the corresponding `t*_train.yaml` as starting point, so the `START_ITER` shouldn't be the same in both files. Please guide.

Thanks

Create sub-issue ▾ 😊

Assignees

No one - [Assign yourself](#)

Labels

No labels

Projects

No projects

Milestone

No milestone

Relationships

None yet

Development

Code with agent mode ▾

[Create a branch](#) for this issue or link a pull request.

Notifications 

Customize

Unsubscribe



JosephKJ on May 15, 2021

Owner ...

Hi Maaz,

The `START_ITER` that you are referring to is the iteration from which we start the clustering process. Kindly note that we dont do clustering while finetuning. Kindly see [this flag](#).

I am afraid that you are confusing this with [MAX\\_ITER](#), which controls the number of iterations that the model is trained for.

Kindly let me know whether this clarifies your doubt.

Thanks,  
Joseph

# Reason for the slow response last month #35

Edit

New issue

📄

🔒 Closed



JosephKJ opened on May 8, 2021

Owner ⋮

Hi all,

My apologies for the slow response during April 2021. I was seriously hospitalized with COVID pneumonia. I lost 20 % of my lungs to the virus. I am improving now. Please find the discharge summary attached along, if that helps you to understand better.

[discharge\\_summary.pdf](#)

Thanks,  
Joseph

Create sub-issue ▾ 😊

📄 🗂️ JosephKJ mentioned this on May 8, 2021

🔒 [resolved] Can anyone reproduce the results? (my results attached) #26

🔒 🗂️ JosephKJ closed this as **completed** on May 11, 2021



qianyizhang on Sep 17, 2021

⋮

stay strong!



Assignees

No one - [Assign yourself](#)

Labels

No labels

Projects

No projects

Milestone

No milestone

Relationships

None yet

Development

📄 Code with agent mode ▾

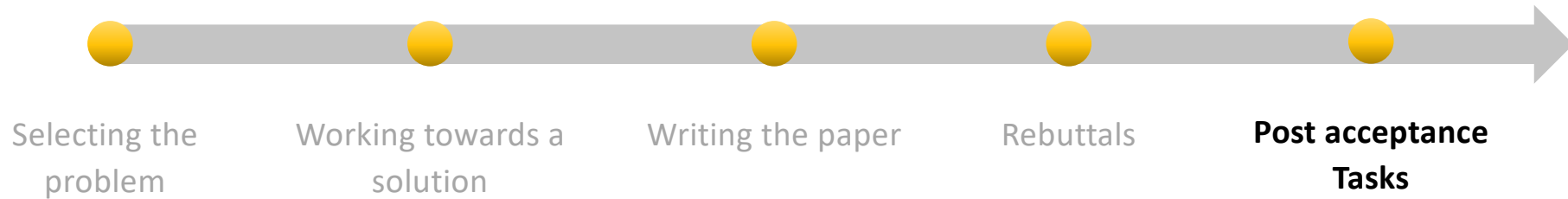
[Create a branch](#) for this issue or link a pull request.

Notifications 

Customize

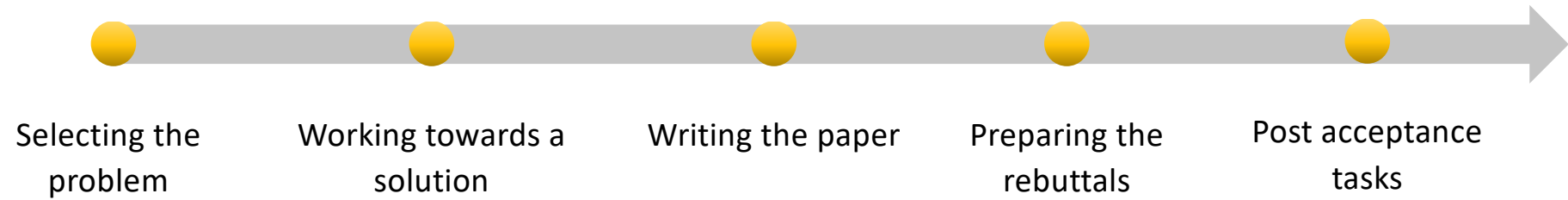
🔔 Unsubscribe

You're receiving notifications because you're



- Make a webpage, YouTube video etc.
- Made your code and models public.
- Prepare for your talk and presentation well: giving a 5 mins talk is harder than giving a 30 mins talk!
- Plan your travel!

# Milestones



# Failures are blessing-in-disguise

The whole system is noisy, please don't take it personally. Improve your work and move on.

Don't give up easily

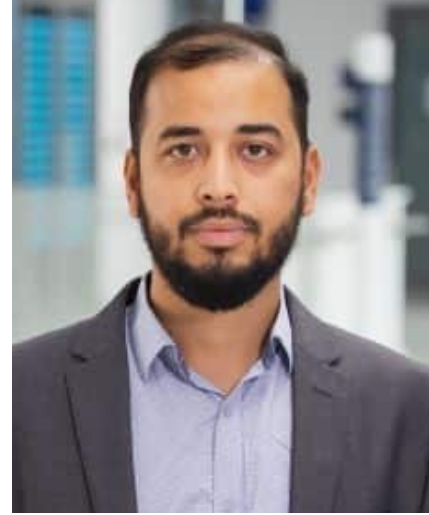
If you truly love what you are doing, and own it, you will not let go of it.



Vineeth N Balasubramanian



భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్  
भारतीय प्रौद्योगिकी संस्थान हैदराबाद  
Indian Institute of Technology Hyderabad



Salman Khan



Fahad Khan



جامعة محمد بن زايد  
للذكاء الاصطناعي  
MOHAMED BIN ZAYED UNIVERSITY  
OF ARTIFICIAL INTELLIGENCE

PhD days are the best phase of your life,  
enjoy every bit of it!



Thank you!