Resilient Machine Learning

https://dsco.usfdatainstitute.org, March 2023, San Francisco

Oliver Zeigermann

Slides: https://bit.ly/dsco-resiliency-2023

PDF: https://github.com/DJCordhose/ml-resources/raw/main/pdf/Resilient%20Machine%20Learning.pdf

Gauge by show of hands

What do you think it most important in a machine learning project?

Please be as open as possible

Questions and comments are welcome ***at any time***

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5. know if it makes sense to bring something into production in the first place
6. have a way of knowing if a production model is still good (and knowing how to act upon that insight)

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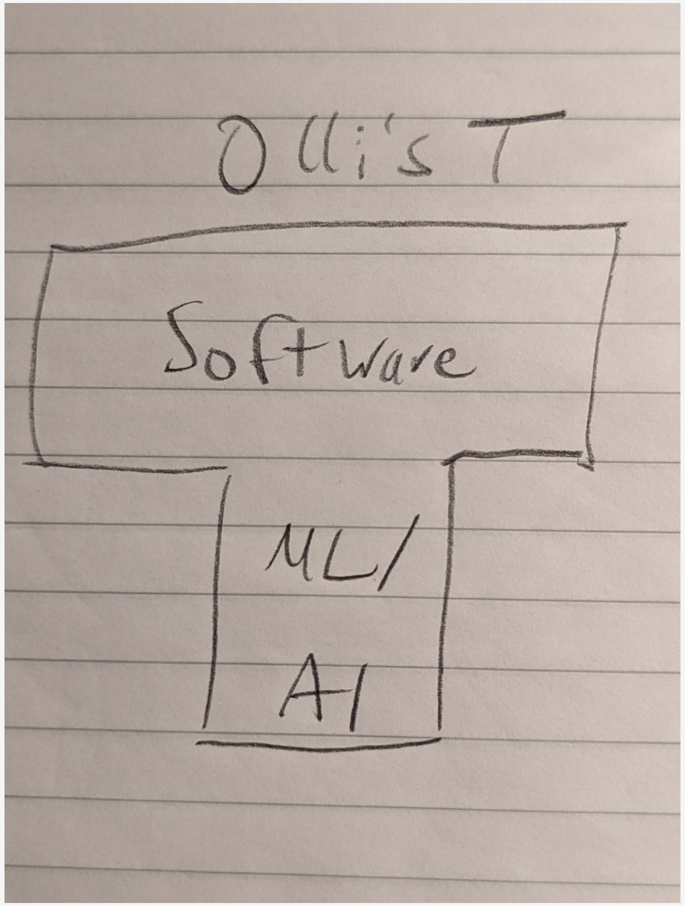
Who is Olli



Oliver Zeigermann: Blue Collar Architect(ML)@OPEN KNOWLEDGE

Resilience

ability to adapt to difficult or unexpected situations

https://en.wikipedia.org/wiki/Resilience

Resilience in the world of Machine Learning

Dealing with Uncertainty

Agenda

1. managing uncertainty
2. deploying machine learning services
3. adversarial attacks and stability
4. drift and monitoring

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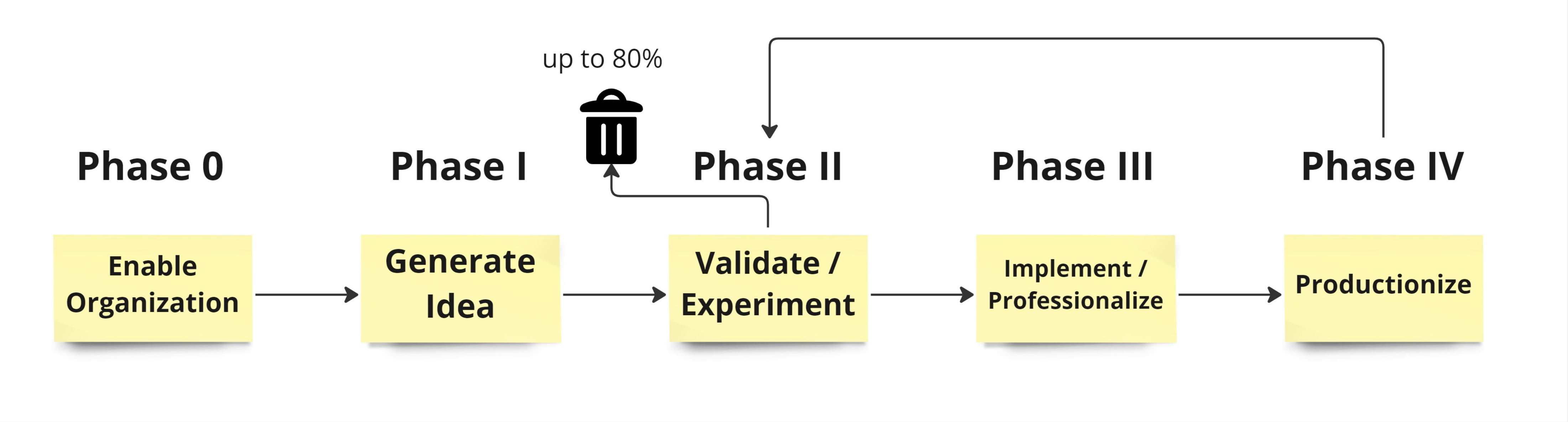
ML comes with a lot of uncertainty

- model and training
  - score
  - confidence
  - training vs test vs out of sample, real world
- will the approach work at all
  - depends on what "work" means
  - what score is good enough?
  - what about the other requirements

Uncertainty is hard to bear

- emotionally
- risk for business
- You need to manage the uncertainty / introduce resilient concepts to handle the stress
- also relevant for development process
  - create PoC, work in phases
  - try and infer life time of model

Machine Learning Projects can be structured in phases



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2. ***deploying machine learning services***
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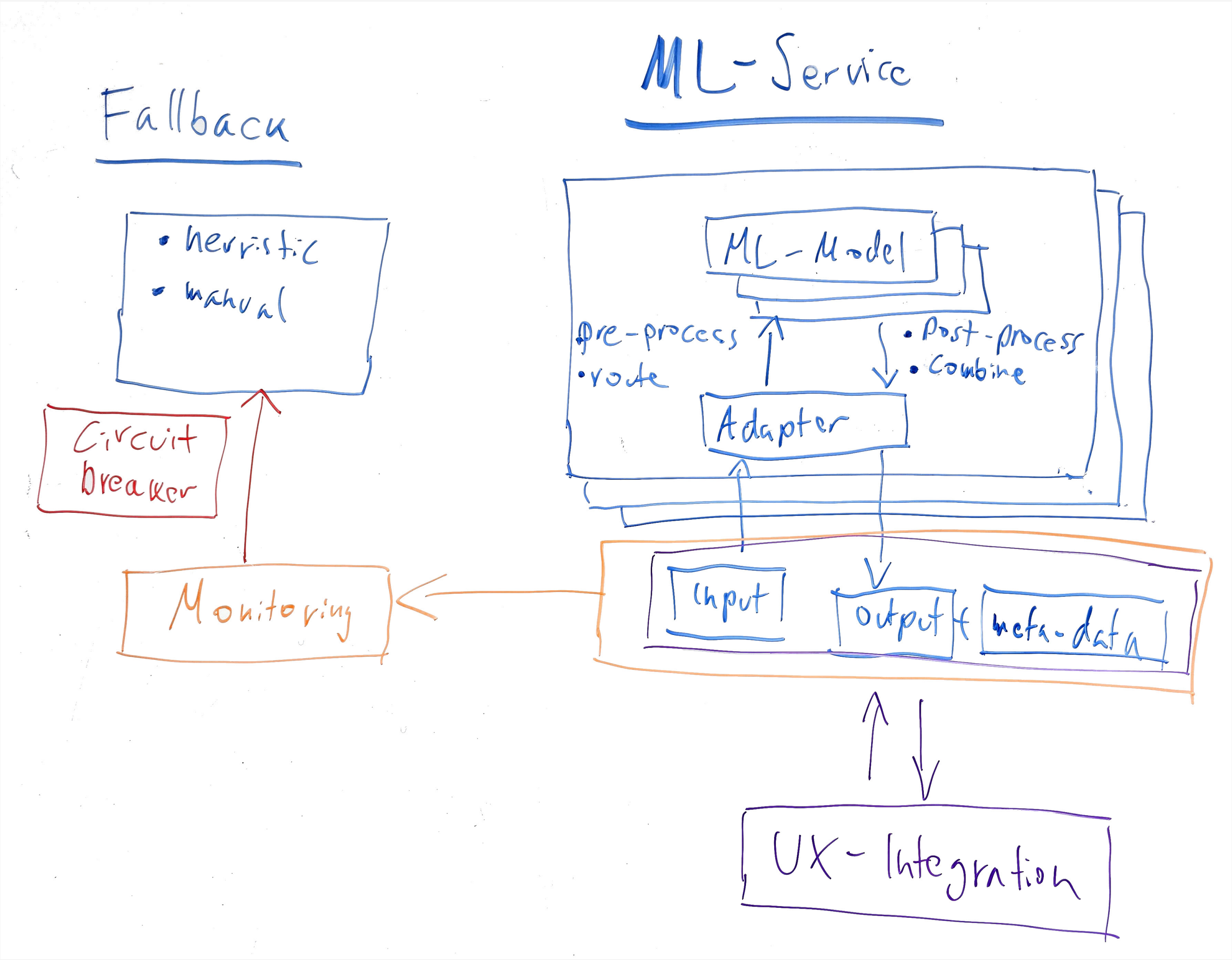
- out-of-sample evaluation typically only possible in production

You don't just deploy the model



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5. ***Robustness against drift*** - the world changes, our model should follow

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Hacking the system / Adversarial Attacks

https://www.instagram.com/reel/CkQUhLov9_u/?igshid=MDJmNzVkMjY=

Hacking the system is more common than you might think

taxes, laws, regulations, contracts, embargoes

- this is actually the job of a lot of people
- transparency vs hackability

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  - often directly contradicting properties like explainability

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  - unwanted disruption for users

Adversarial AE detector

still able to detect the adversarial examples in the case of a white-box attack where the attacker has full knowledge of both the model and the defence

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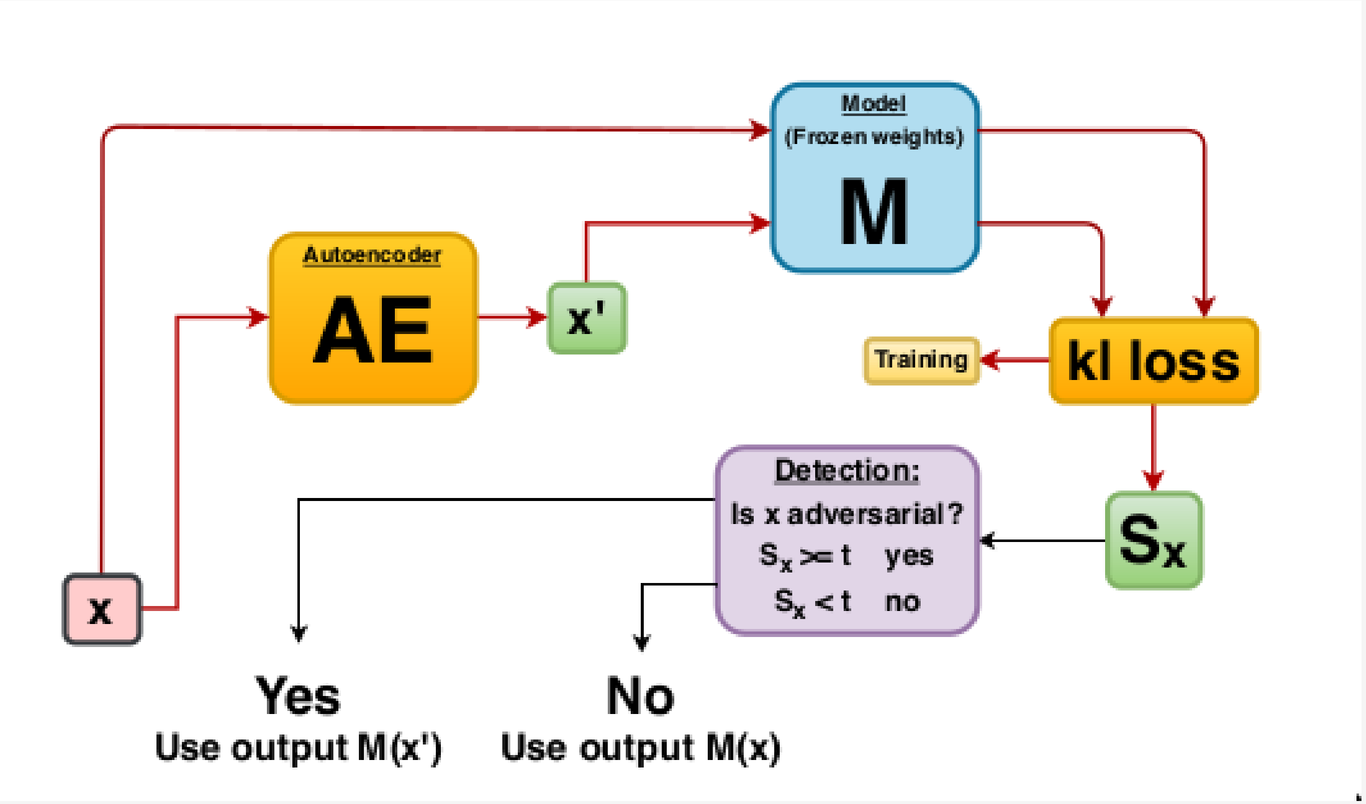

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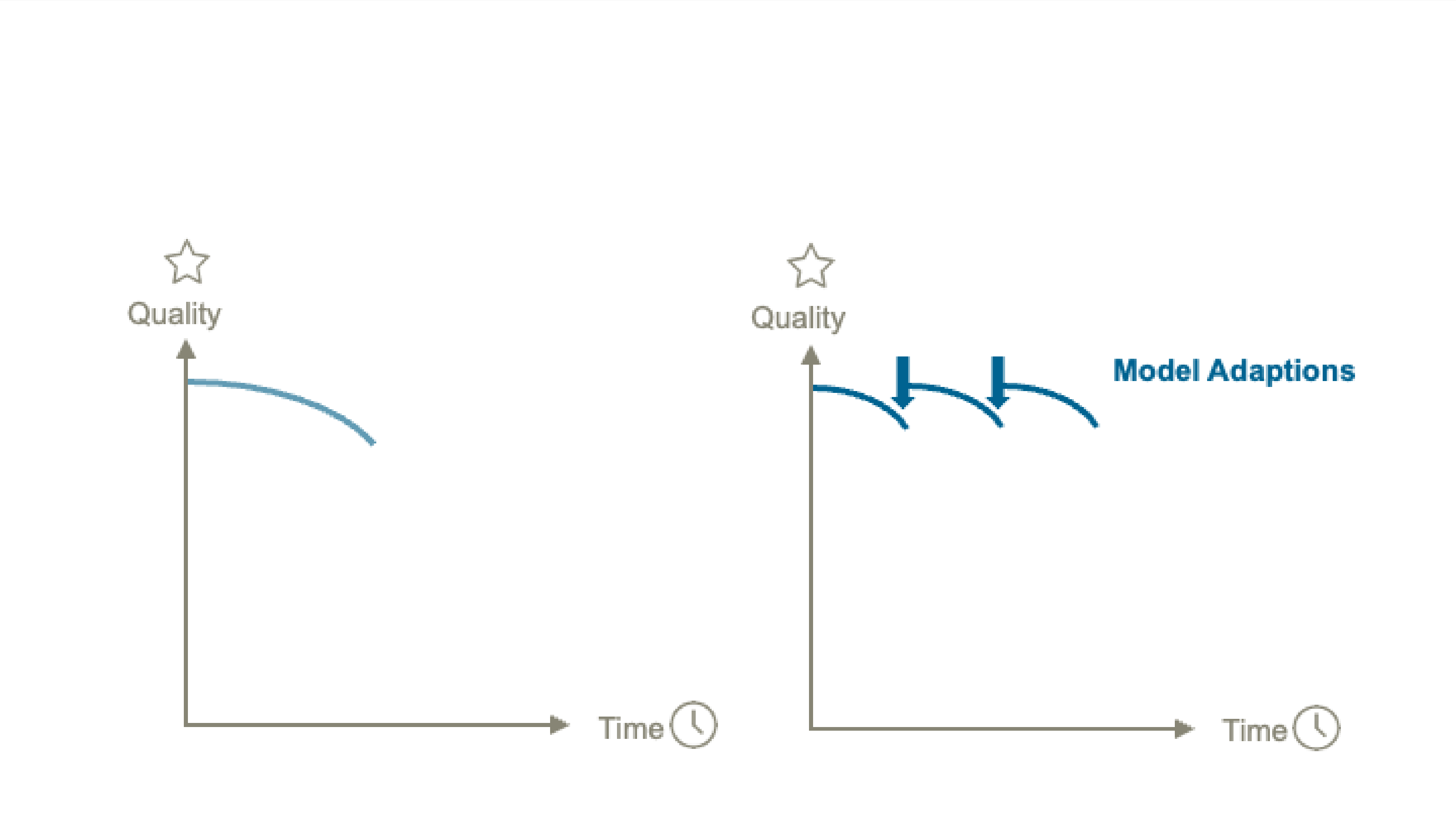
Machine Learning Systems are dynamic in nature



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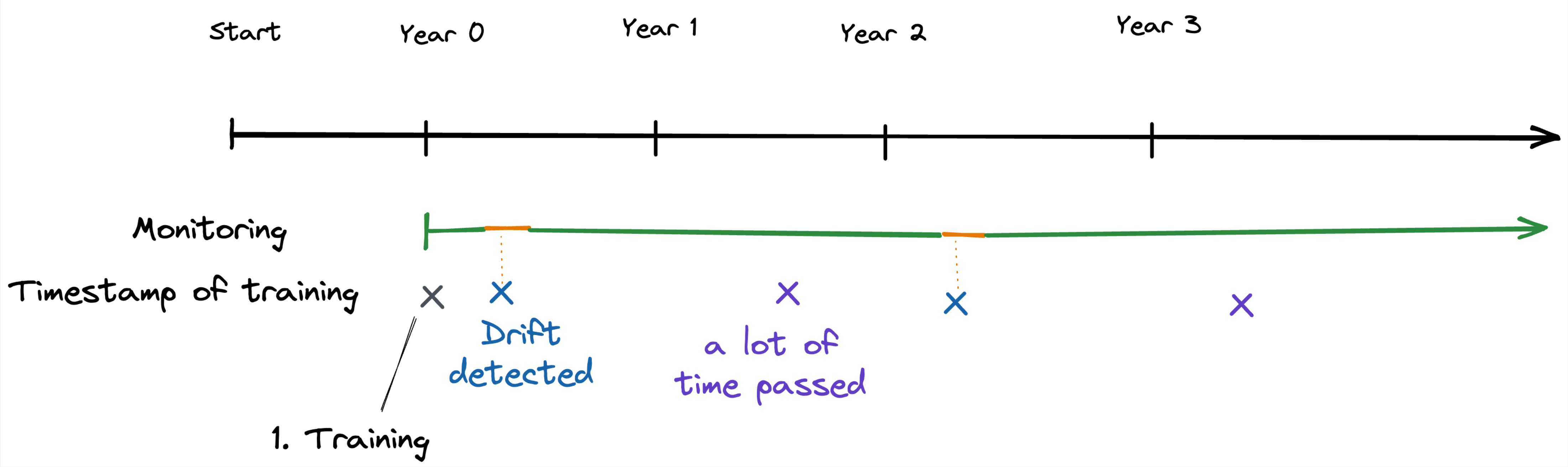
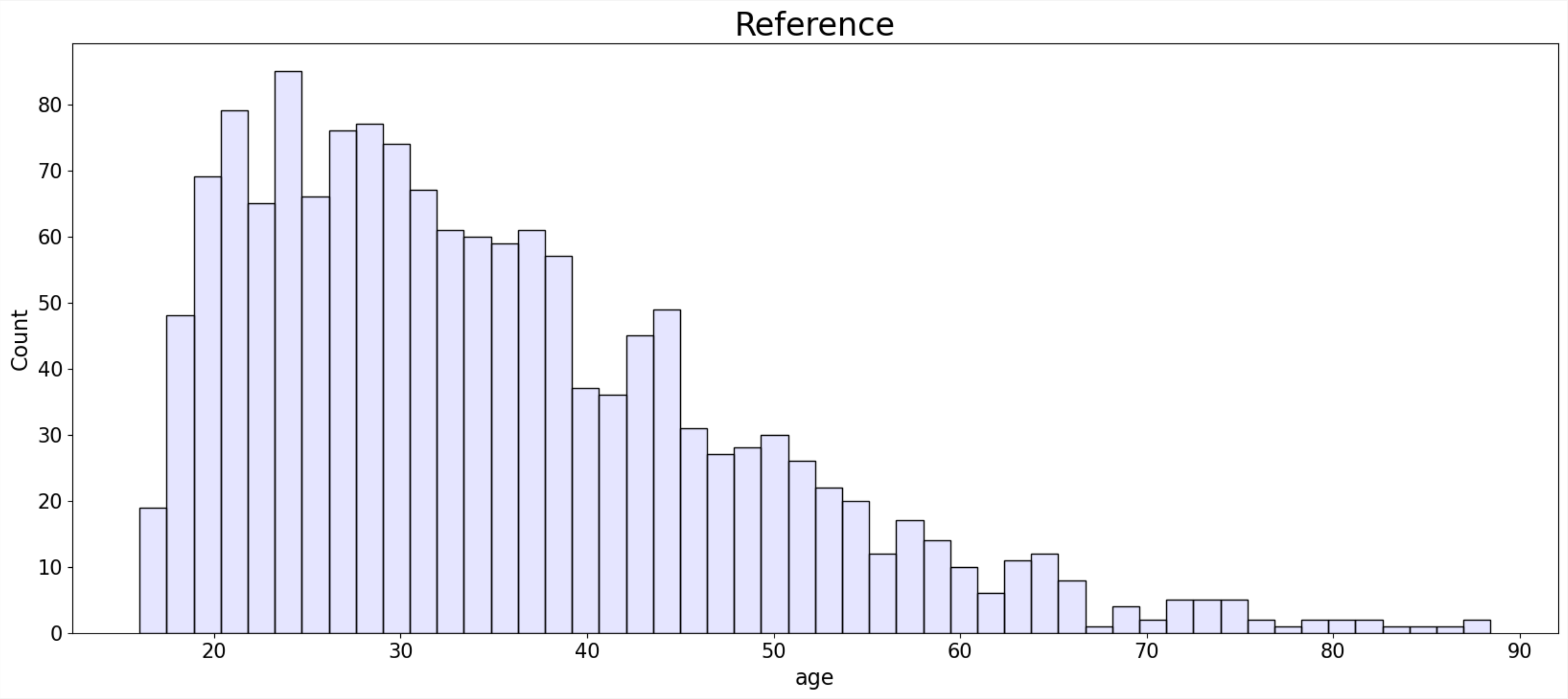
- ***When the distribution of prediction data is significantly different from that of training***

At time of training?

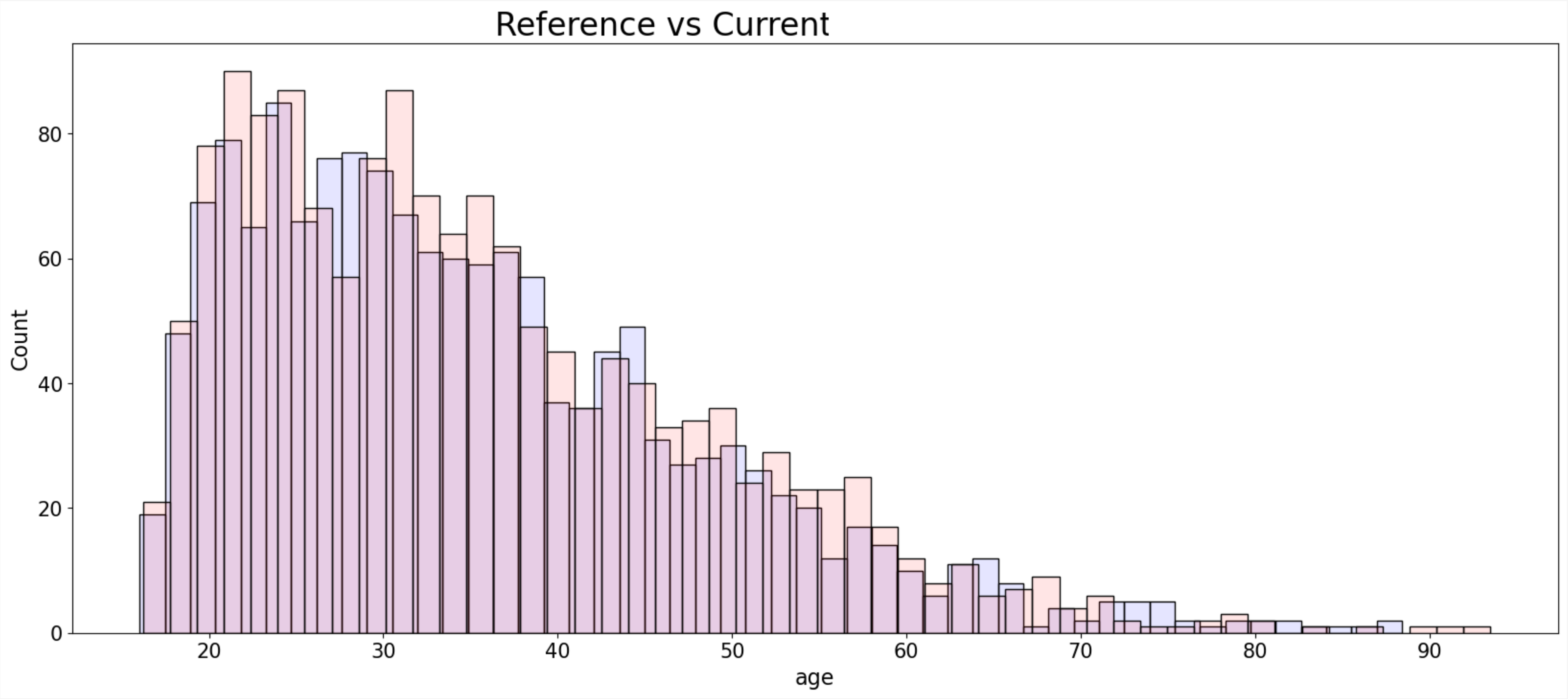


Reference Distribution

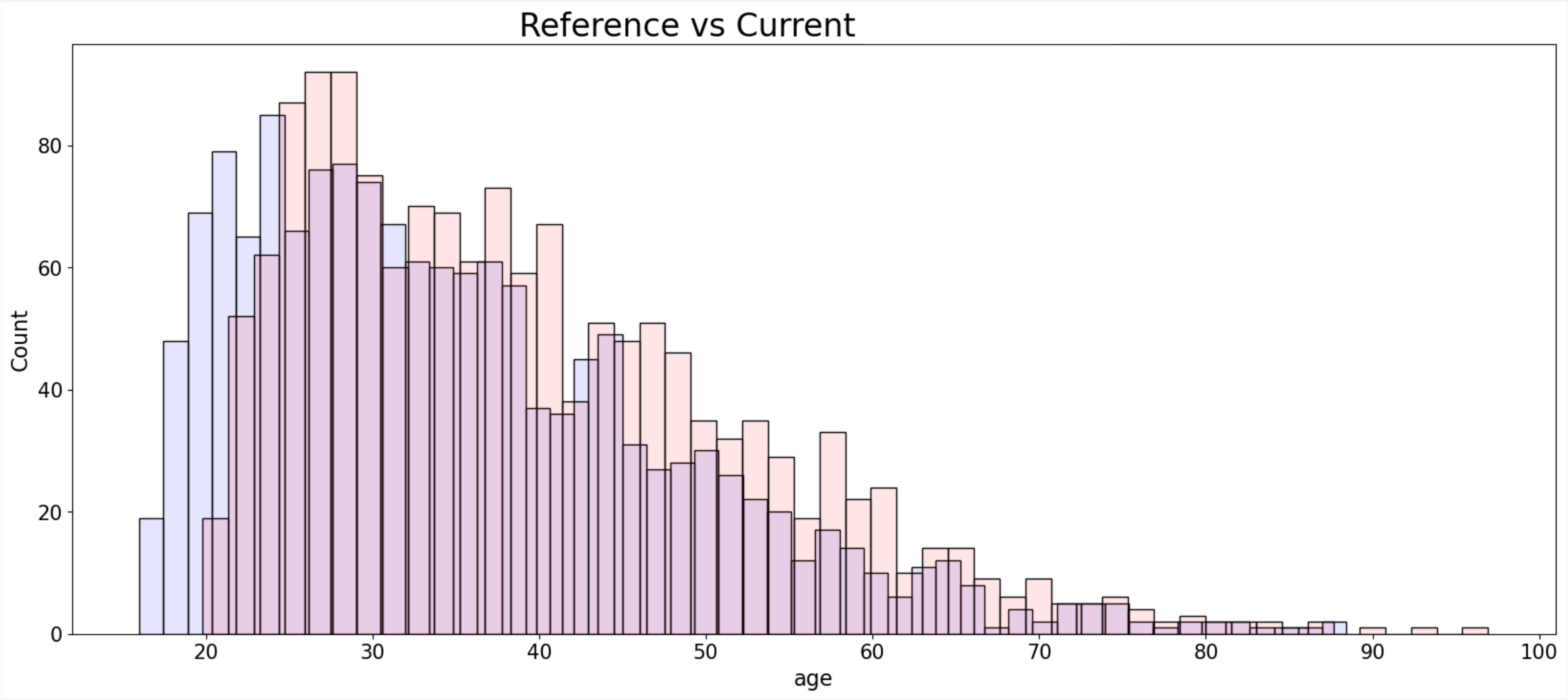


Example: Age of people seeking for insurance

Does it drift?



And this?



Reference vs Current
Count
age
0
20
40
60
80
20
30
40
50
60
70
80
90
100

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- scores, like p-values often are not very intuitive

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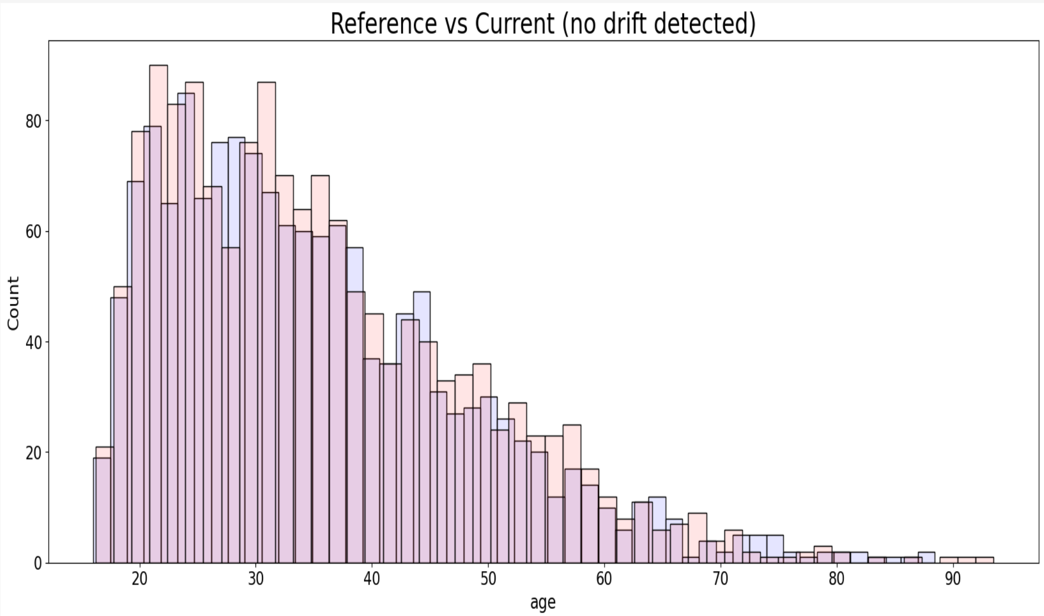

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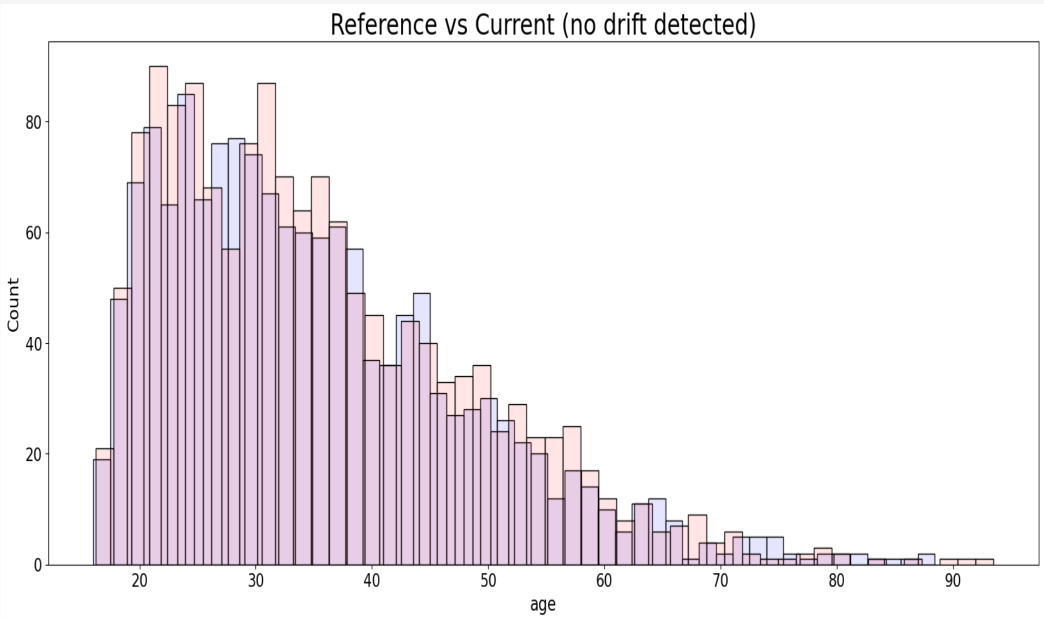

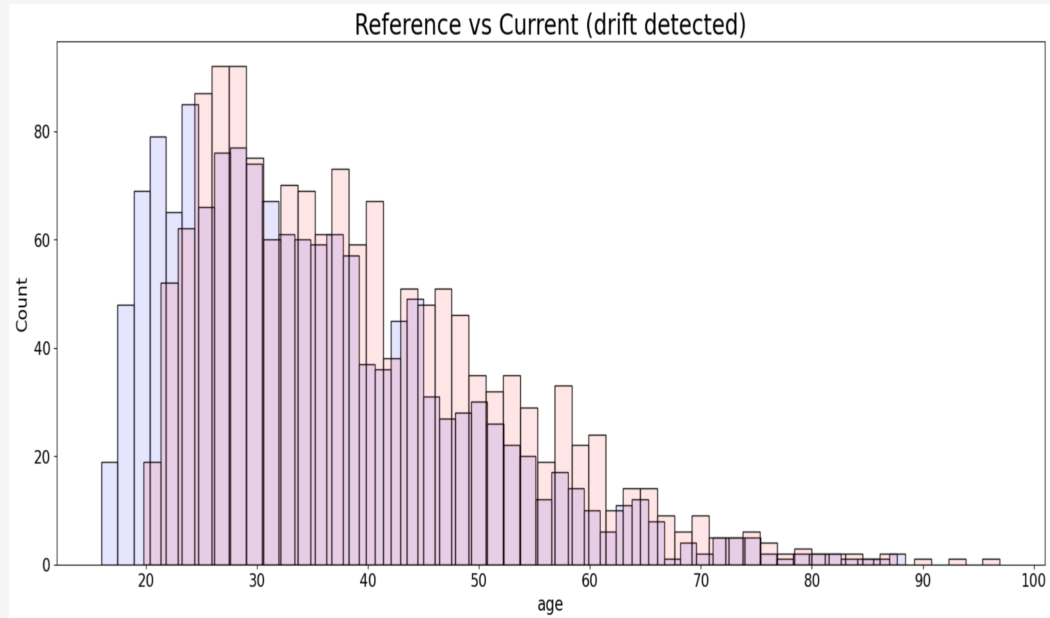

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  - Heuristics / Baseline

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Drift Detection in Images

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- dimensionality reduction to multivariate data
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- drift detection via distilled model
  - similar to adversarial attack detection

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- practitioners need statistical skills

Thanks a lot

Resilient Machine Learning

Stay in Contact

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