



Taking Research Into Production

Anant Nawalgaria

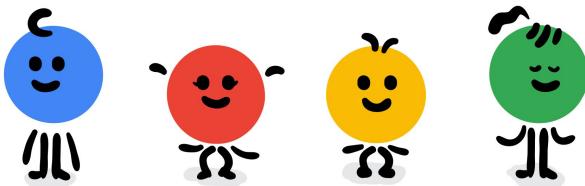


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Second Order Personalization with RL..



Scoped into a simplified RL problem

Top Beiträge
Die beliebtesten Beiträge der Woche

Beliebte Produkte im Ausverkauf
Aktuell gefragte Produkte zu Aktionspreisen

Aktuelle Aktionen
Die beliebtesten Angebote auf einen Blick

Aktuelle Bestseller



12 possible article/
product recommenders
to choose from based on
the context



Value of Vertex AI

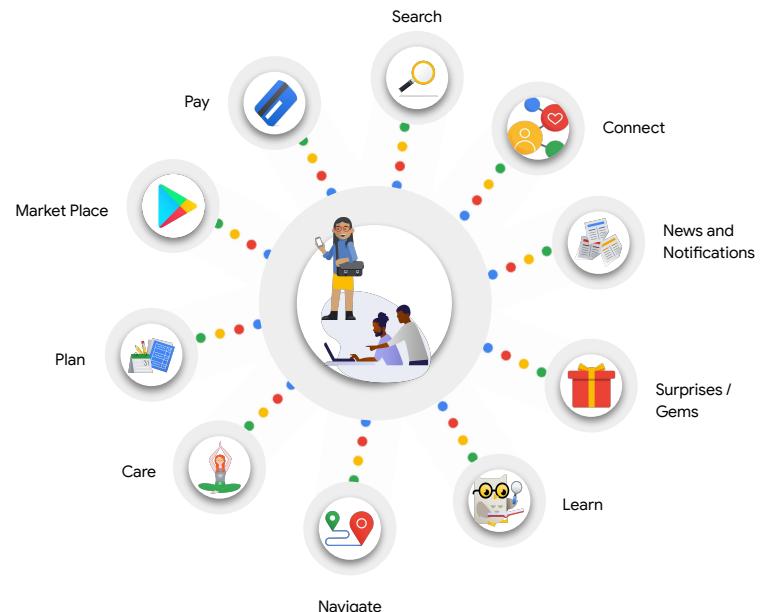
How Digitec Galaxus delivers personalized newsletters with reinforcement learning and Google Cloud

"As a result, even the software engineers on our team without much ML expertise feel confident... The data scientists are able to spend more of their time ..delivering more value to the users and the business"

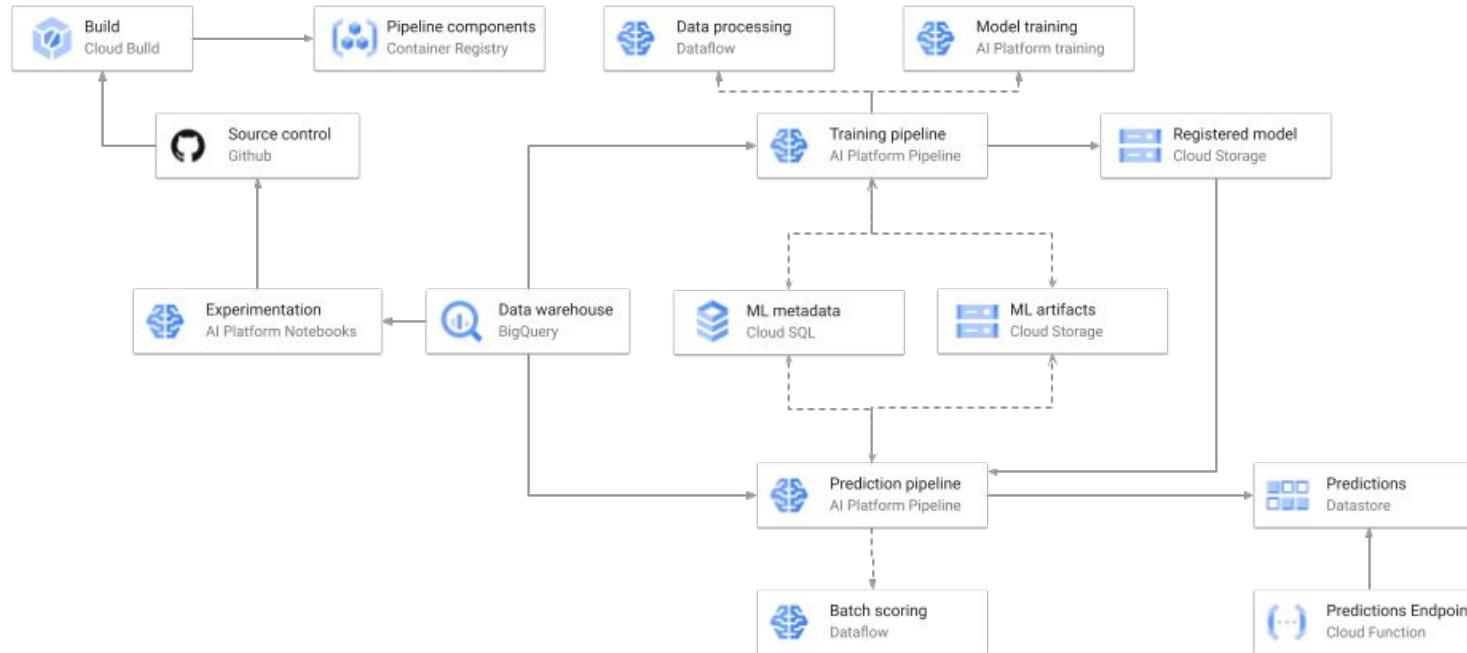
Christian Sager



- **Galaxus is the largest Swiss online shop**
 - steadily growing range of products for almost all daily needs
 - offering consistently low prices
 - fast, reliable and free delivery
 - winners of several awards.
- **Use Case:**
 - Increase the user engagement for their newsletters by finding the best recommenders system to use for each user, and personalizing it.



Target architecture: Full stack on GCP



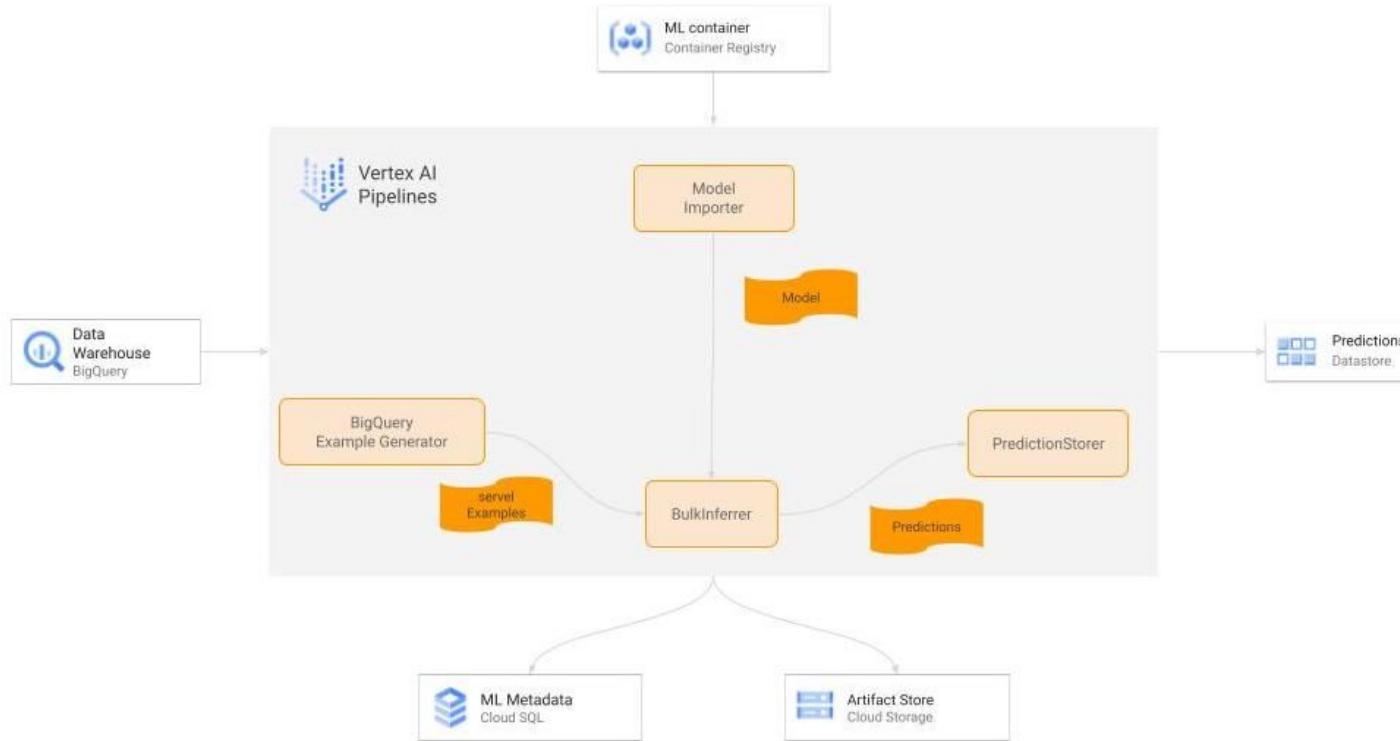
Contextual Bandits with [TFX](#) and [TF-Agents](#) on GCP

Continuous Training Pipeline (monthly)



Contextual Bandits with [TFX](#) and [TF-Agents](#) on GCP

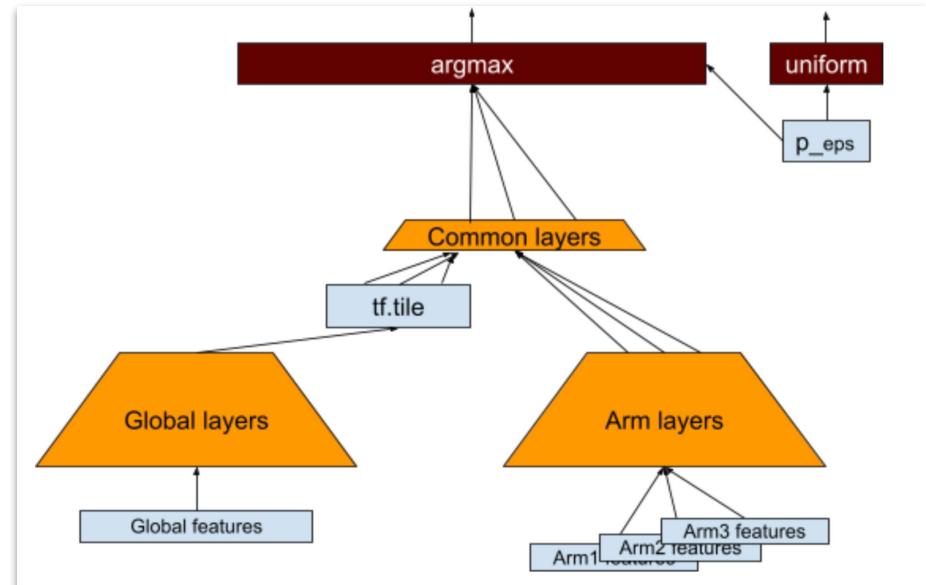
Daily Inference Pipeline



Why Contextual Bandits?

Advantages:

- Model generalizes over items.
- Easy to add new items on the fly.
- Number of actions can vary.
- Exploration strategy takes care of the biases coming from the prod policy.
- Performance guarantees (regret).
- Multi Objective & Constrained Optimization possible
 - E.g. Increase user engagement while keeping opt-outs stable

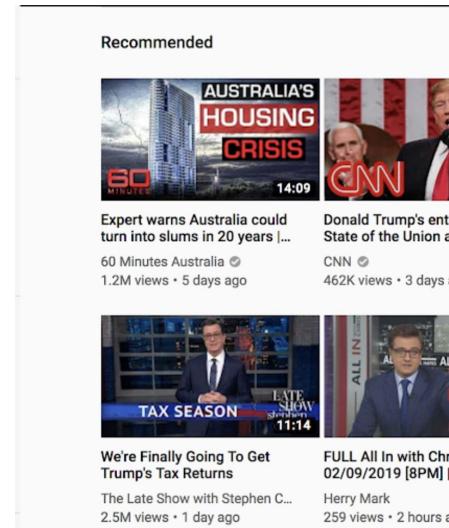


Example for an *eps*-Greedy model with per arm features

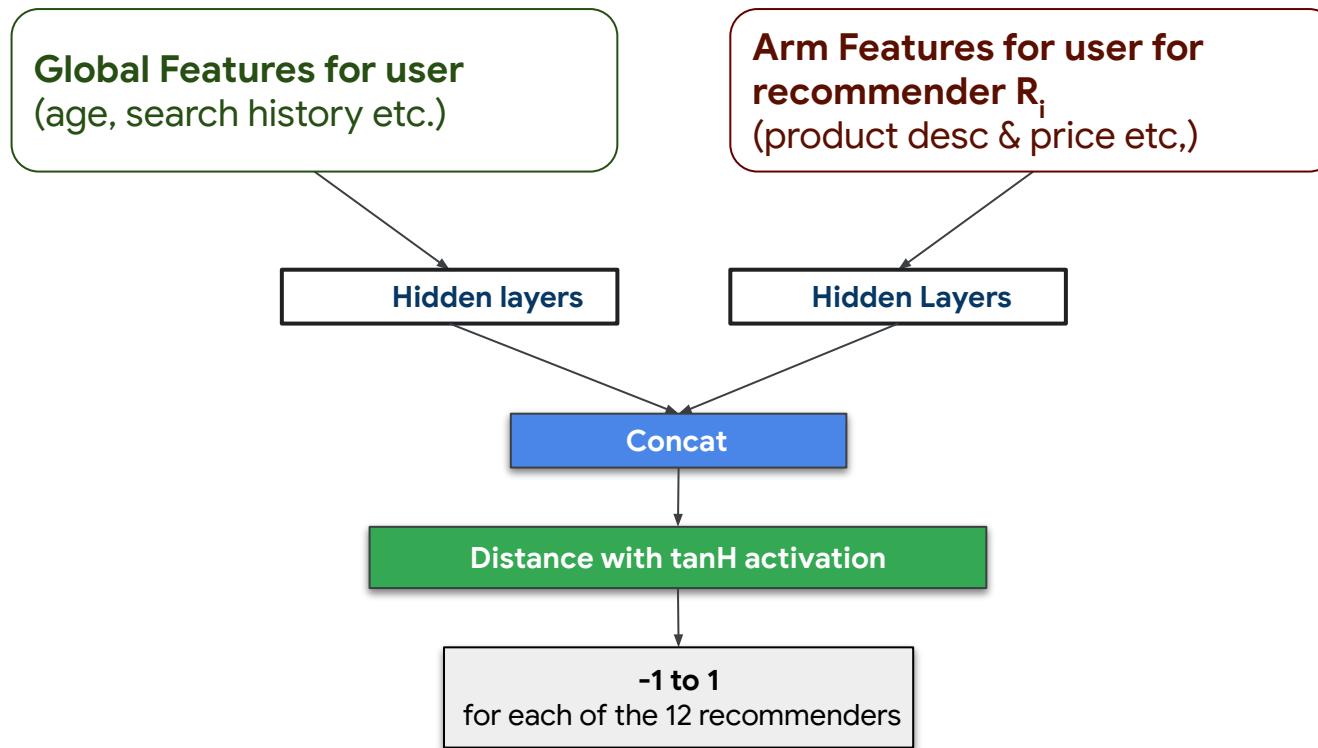


Features for Bandits for Recommendation

- **User Features:**
 - Demographics, Time(Week/Month), Type of user, 1 month, Search history, product bought (different levels of taxonomy) etc
- **Items:**
 - Item features for each of Item1, item2, ...
 - genre, length, popularity, ...
- **Actions:**
 - The type of Recommender based on exploitation
- **Rewards:**
 - CTR, money spent, etc...
 - $-1 + \text{unsubscribe}$, $1 = \text{click}$

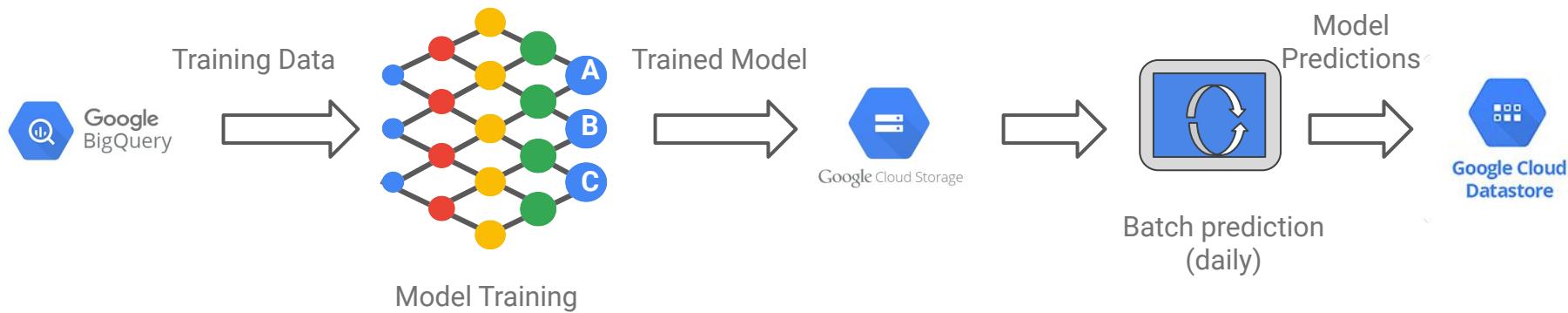


Contextual Bandit Architecture

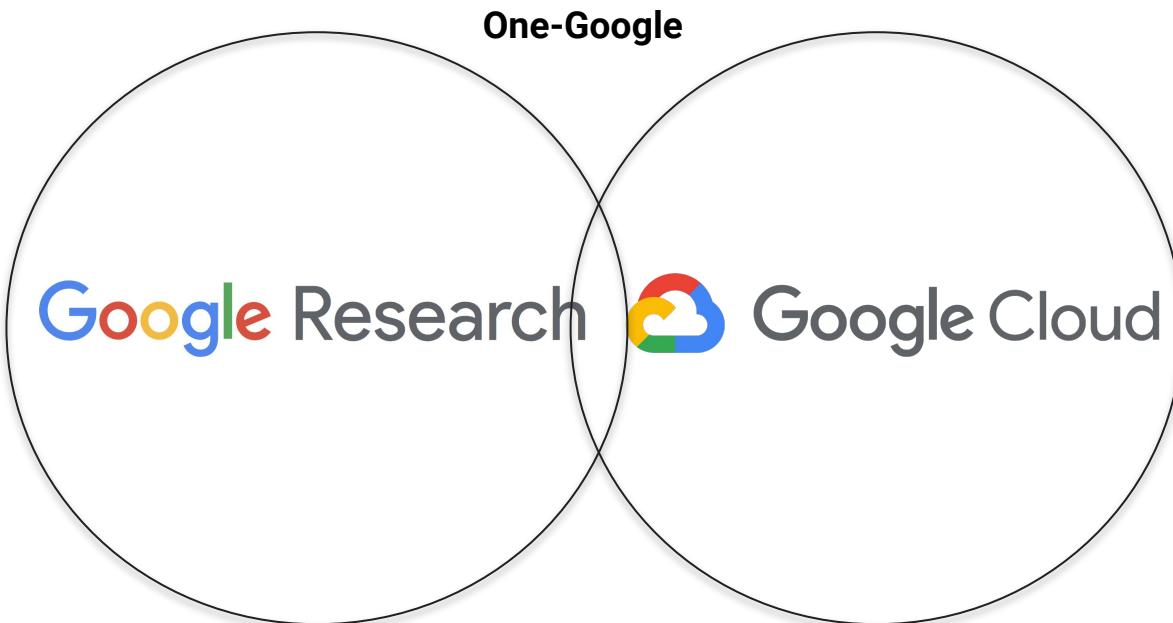


Contextual Bandits with [TFX](#) and [TF-Agents](#) on GCP

- **Production-ready & scalable** TFX pipeline orchestrated by Kubeflow Pipelines
- Training data extracted from [BigQuery](#)
- The training pipeline & batch prediction runs on [AI Platform Pipelines](#)
- [DataFlow](#) for large-scale data processing
- Batch predictions stored on [Datastore](#)
→ Pipeline templates & Technical Design Doc: under development



Highlights



Prod: Serving 2 mil weekly





All TensorFlow Core TensorFlow.js TensorFlow Lite TFX Community

Community · TFX ·

How Digitec Galaxus trains and serves millions of personalized newsletters per week with TFX

August 11, 2021



Posted by Christian Sager (Product Owner, Digitec Galaxus) and Anant Nawalgaria (ML Specialist, Google)



Google Cloud

Semi Supervised Semantic Segmentation (S⁴)..

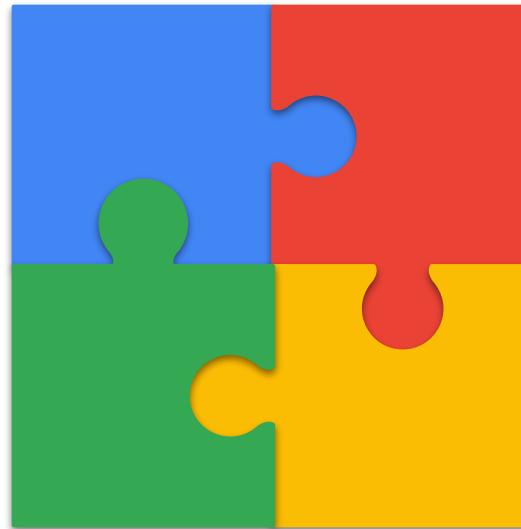


02

The Partnership

Google Cloud

Munich RE

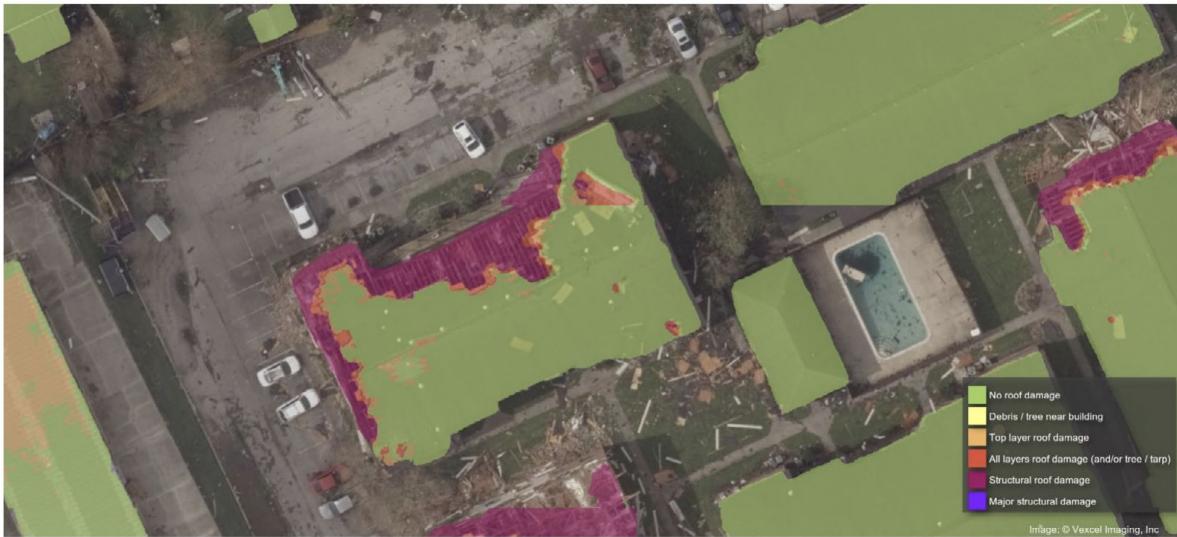


Google Research

Taktile

The use case: Geo Spatial Damage Assessment

Precision Damage Assessment generated by AI
Hurricane Ida - August 29, 2021



Challenges

1

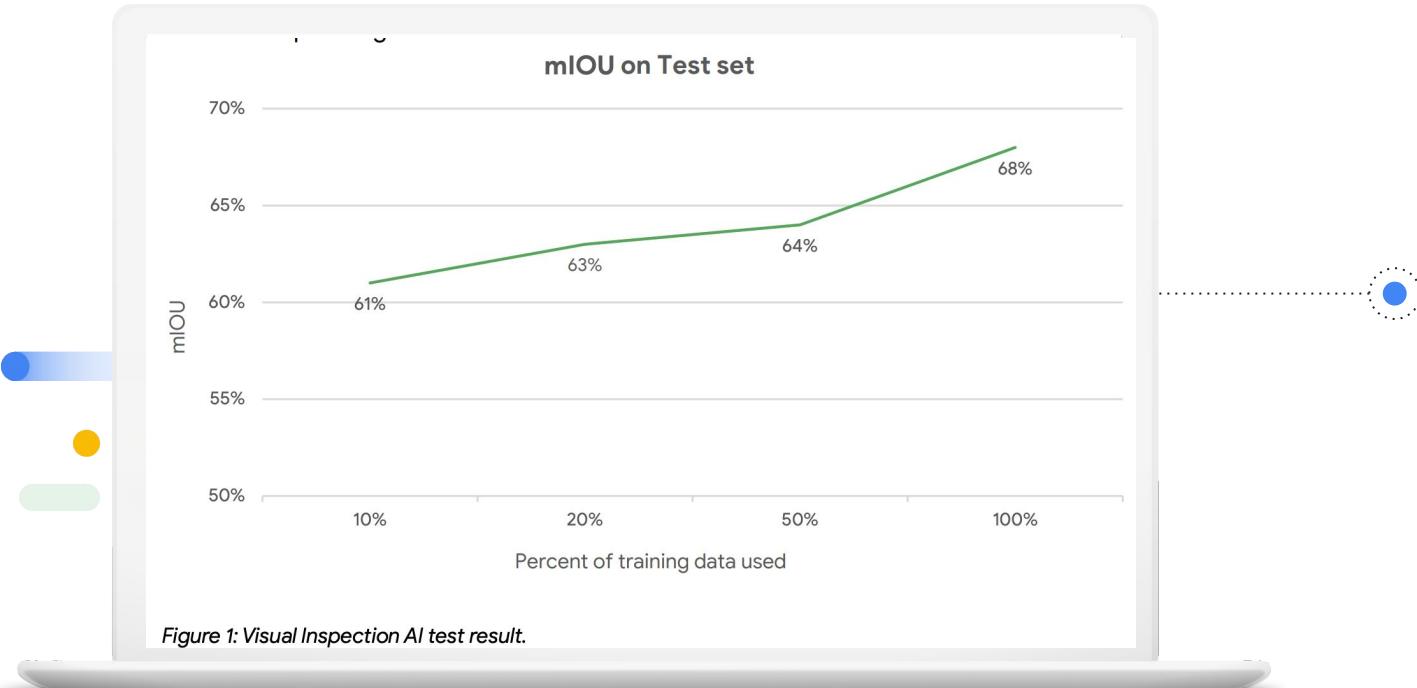
Domain Labelling is
extremely expensive

2

Very time/cost intensive for
developing such models
and training them regularly



Accelerated Productionisable results within hours instead of weeks/months



Challenges with Data Labelling



Manual processing

Standard ML is very Data Inefficient and often requires lots of labelled data to work

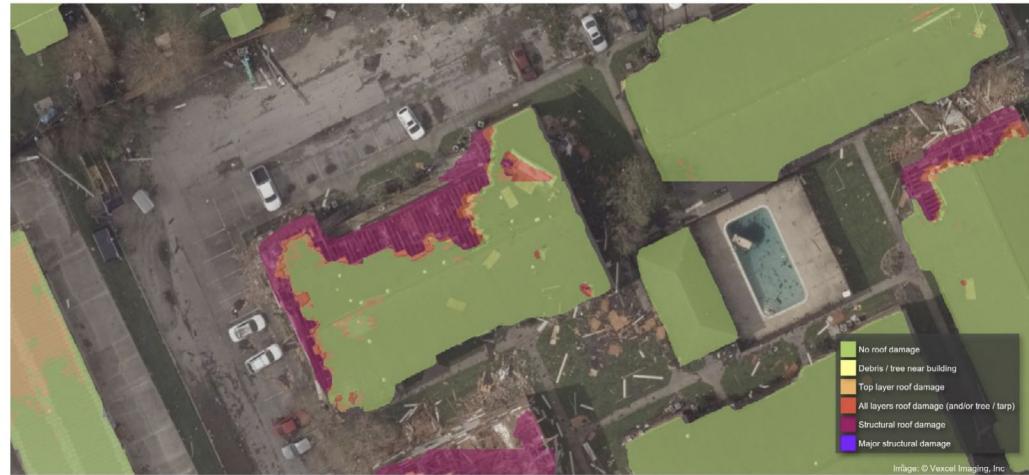
Labelling requires:

1. Domain Expertise
2. Precise labels
3. \$3 or more per label

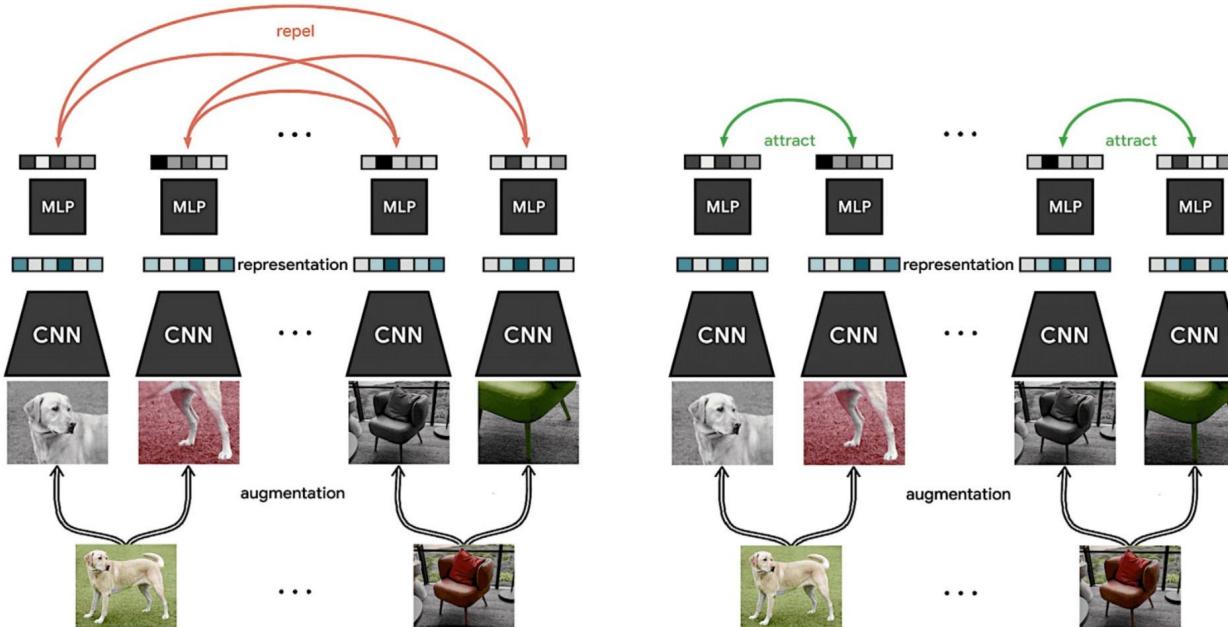


Precision Damage Assessment generated by AI
Hurricane Ida - August 29, 2021

Munich RE



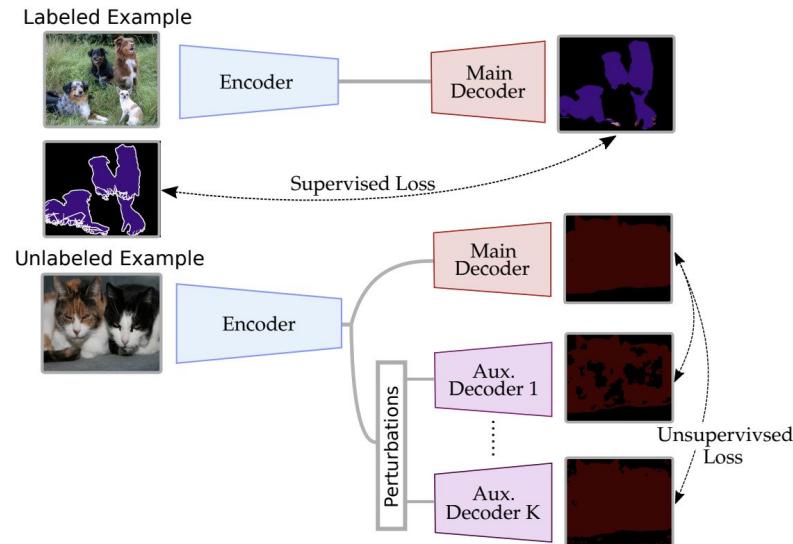
Enter semi supervised learning: SimCLR



Cutting edge field of research in doing more with less (labels)



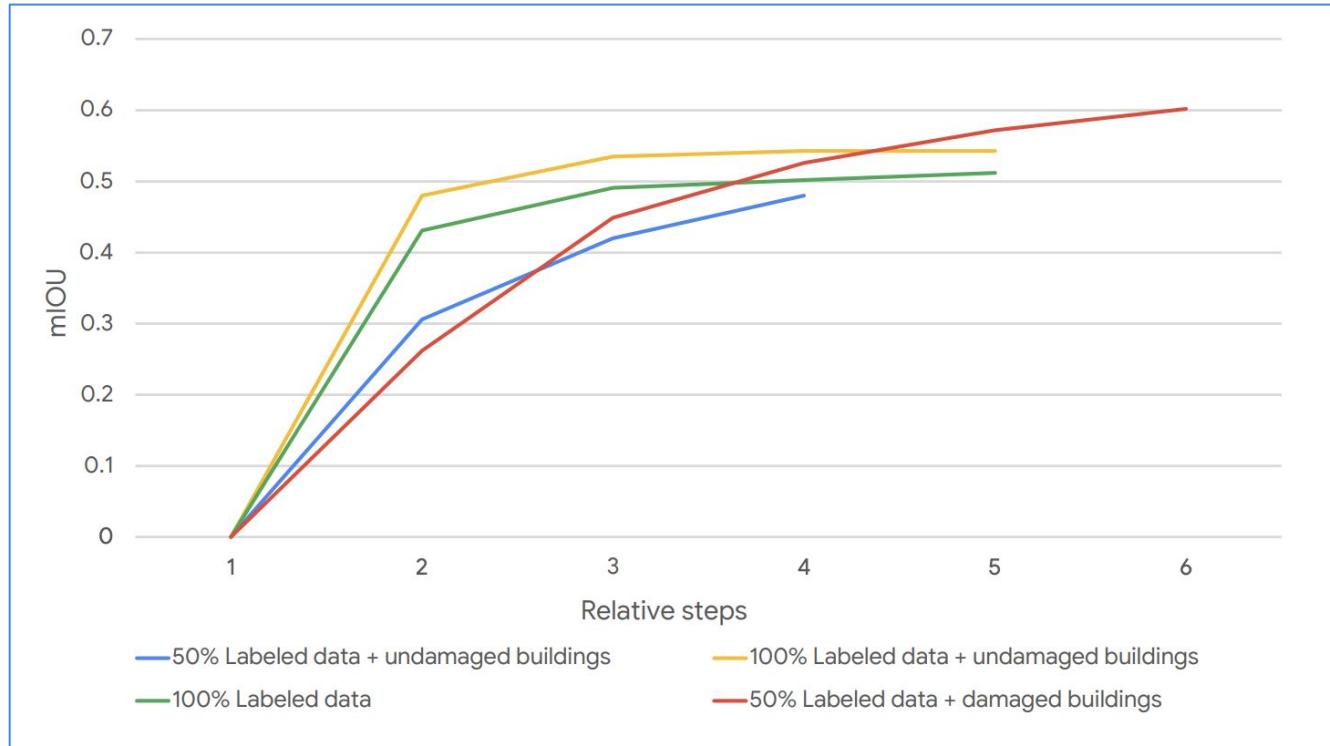
SSL using Cross Consistency Training



Reconstruction of Perturbed Latent spaces



Cost savings for Visual Use cases



- + Same performance for half the labels/cost
- Increased dataset/training time

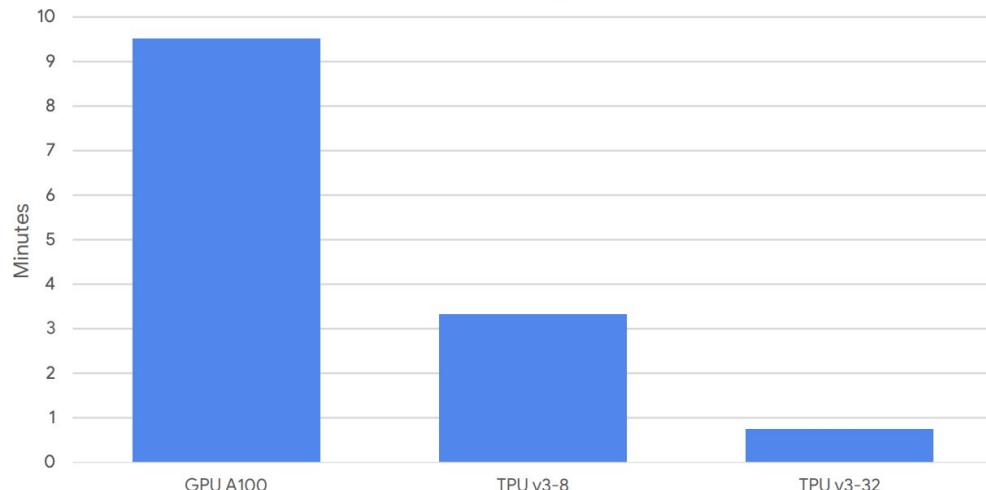


Enter: TPUs

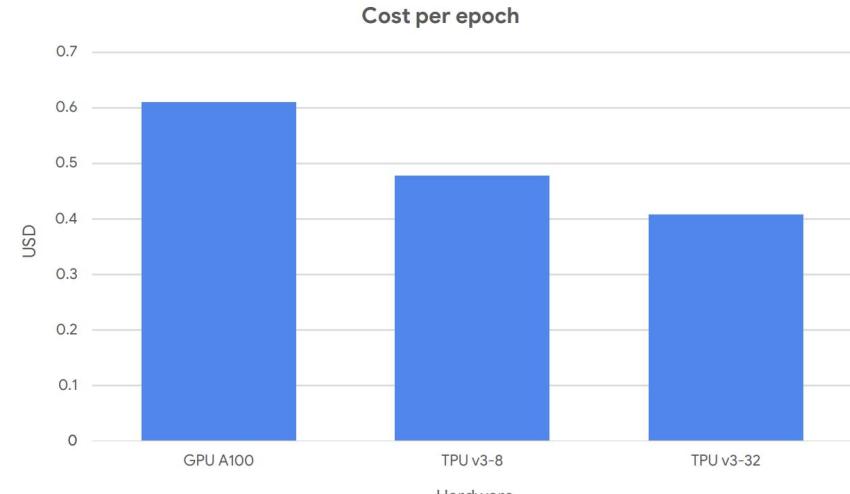


Time & cost savings with just the TPU v3-32

Time per epoch



Cost per epoch



= 18.75x perf/TCO. Much more possible with TPU V4



Key takeaways for your Customer



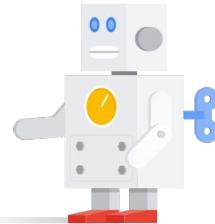
50% Cost savings

For Human labelling



92% Training Time reduction

For Training Semi Supervised Models



18.75x perf/TCO

Considering the time/cost efficiency of TPUs



Accelerated time to market

With Visual Inspection AI



SOTA collaboration

With Cloud & research to be successful



Next steps



Improving the Speed and Efficiency of AI-Enabled Damage Assessment in Insurance

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[Technical Whitepaper](#)

[TPU blogpost featured](#)



Thank You!



Google