



DSF-R

Vienna 2018

---

# Scaling R in the Cloud

**with Azure Batch and Docker**

Christoph Bodner & Thomas Laber



## 01

## 02

## 03

### Topics

#### Who we are

(obligatory marketing stuff...)

Data Science@Post AG:

- Overview: Post AG
- Our team

#### Scaling R with Azure

Using:

- AzureBatch and
- Docker

for development & production

#### Case study

doAzureParallel + Caret:

- Distributed ML
- Easy setup



## 01

## 02

## 03

### Topics

#### Who we are

(obligatory marketing stuff...)

#### Data Science@Post AG:

- Overview: Post AG
- Our team

#### Scaling R with Azure

#### Using:

- AzureBatch and
- Docker

for development & production

#### Case study

#### doAzureParallel + Caret:

- Distributed ML
- Easy setup

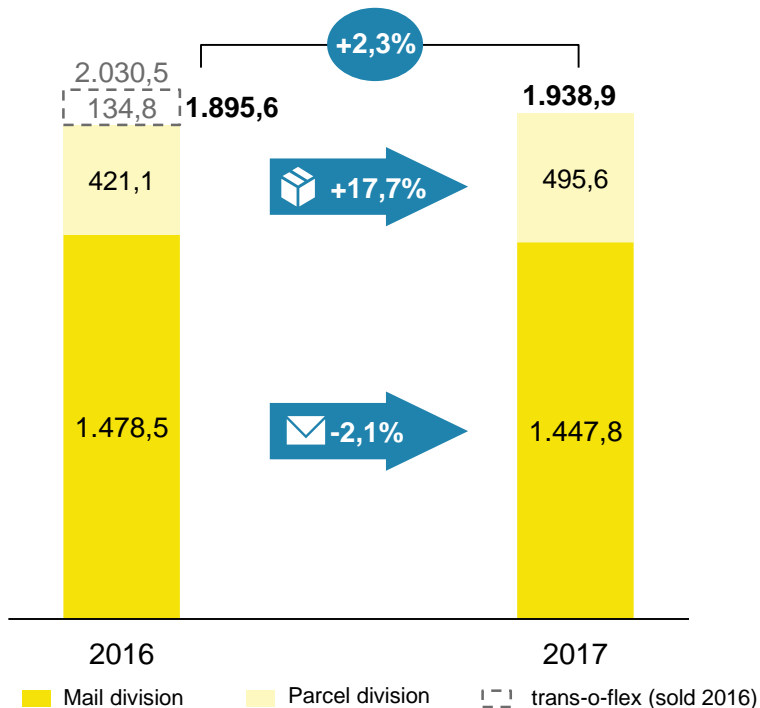


# OVERVIEW: POST AG

## COMPANY PERFORMANCE & PARCEL VOLUMES OVER TIME

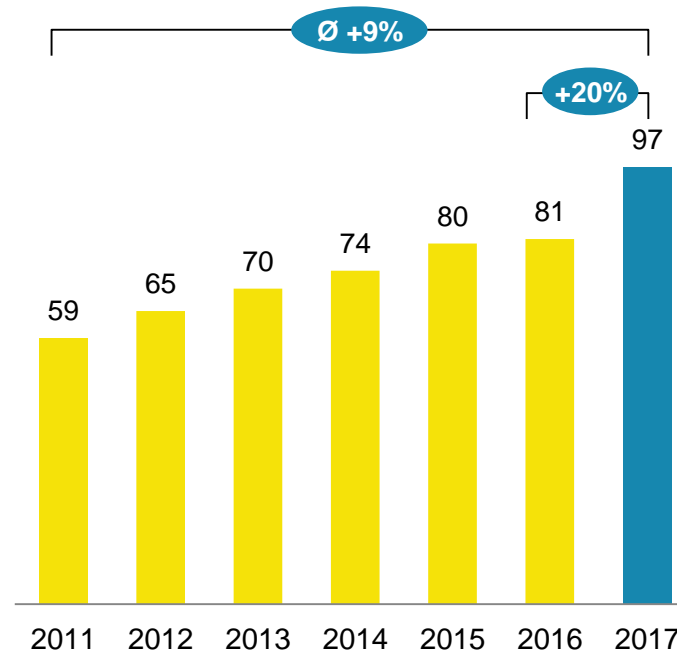
### SALES PERFORMANCE

mio EUR



### PARCEL VOLUMES OF AUSTRIAN POST

mio parcels



# OUR TEAM

## PEOPLE WHO LIKE $\pi z^2 a$ IN EVERY FORM



**Christoph Bodner**

Lead Data Scientist

Quantitative Finance (WU)  
Prev.: KPMG



**Thomas Laber**

Senior Data Scientist

Business Informatics (TU)  
Prev.: Accenture



**Martin Blöschl**

Junior Data Scientist

Computational Intelligence (TU)



**Raphael Pesl**

Junior Data Scientist

Mathematics (TU)



## 01

## 02

## 03

### Topics

#### Who we are

(obligatory marketing stuff...)

Data Science@Post AG:

- Overview: Post AG
- Our team

#### Scaling R with Azure

Using:

- AzureBatch and
- Docker

for development & production

#### Case study

doAzureParallel + Caret:

- Distributed ML
- Easy setup



How can we run  
complex experiments  
quickly?



How can we put  
those models in  
production?

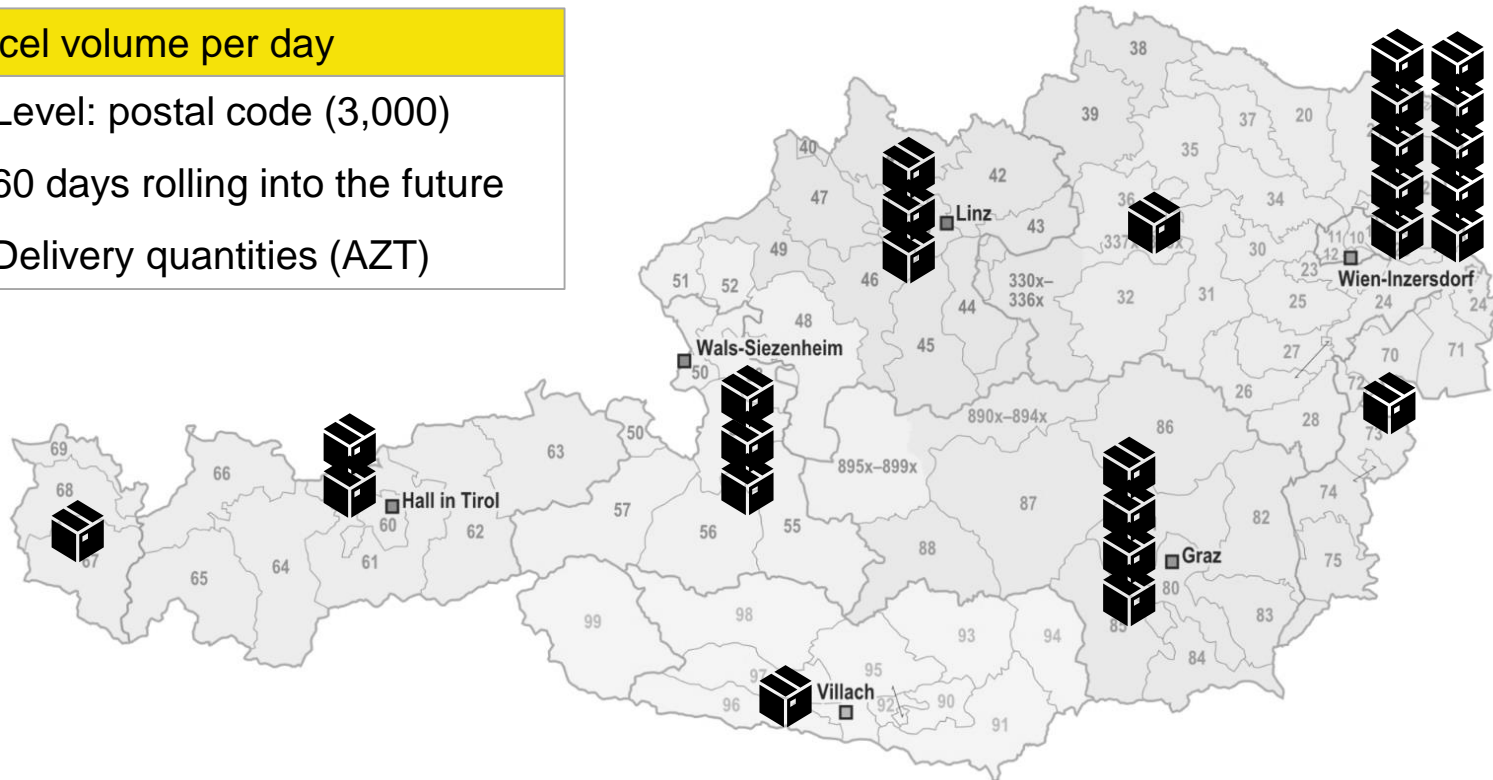


# A SAMPLE PROBLEM

## HOW MANY PARCELS WILL WE NEED TO DELIVER IN THE FUTURE?

### Parcel volume per day

- Level: postal code (3,000)
- 60 days rolling into the future
- Delivery quantities (AZT)



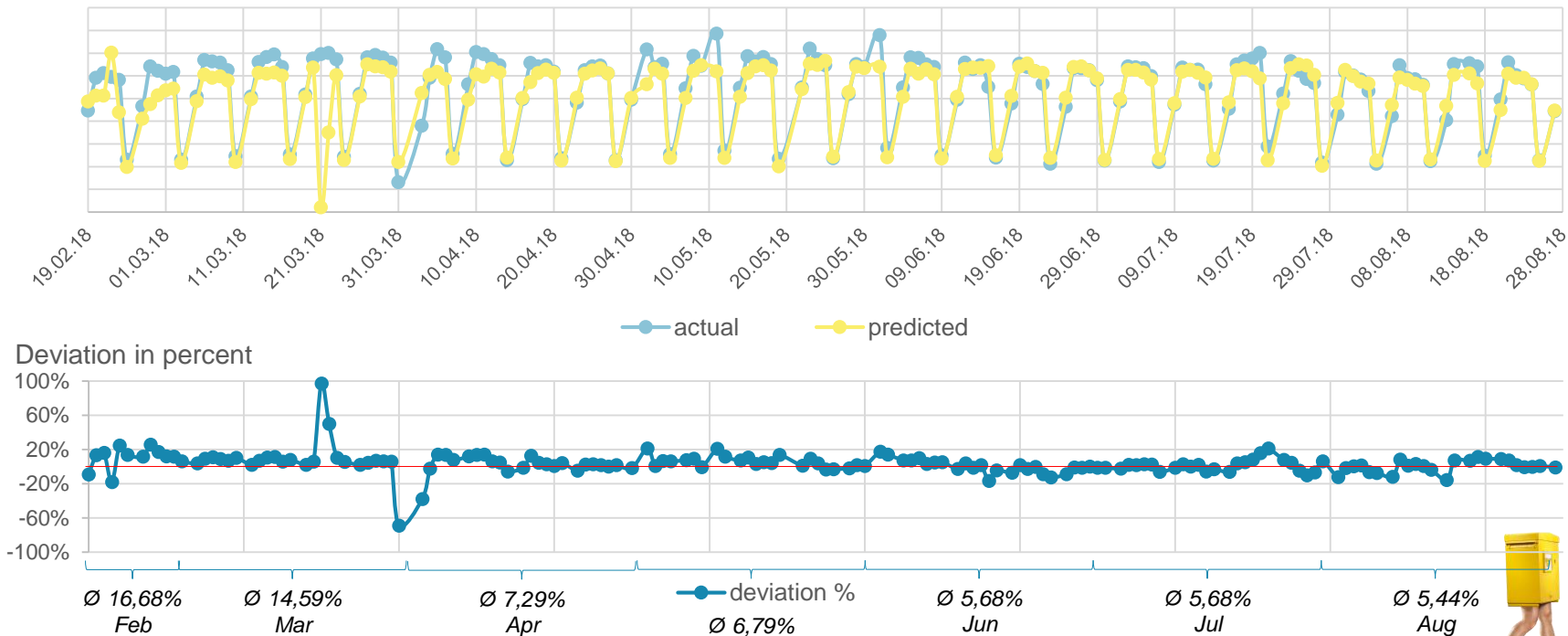


# FORECASTING PERFORMANCE

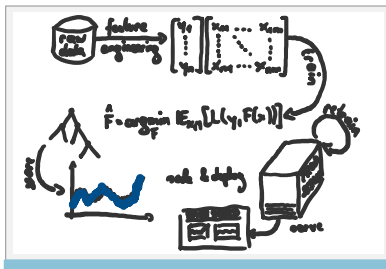
## 7-DAYS-AHEAD

### Performance

Parcel volumes per day Austria (7 days ahead)

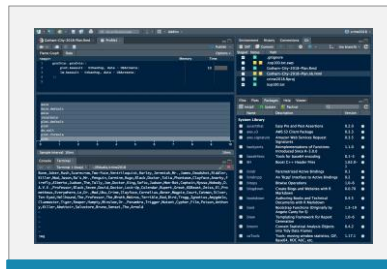


# FROM EXPERIMENT TO DEPLOYMENT OUR JOURNEY



## Whiteboard phase

- Draft architecture
- Modeling strategy
- Everything seems easy 😊



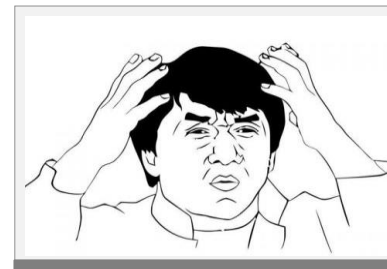
## Experiment phase

- Build model on sample
- Model improves
- Happy Data Scientists



## Deadline phase

- Model training takes too long
- Model gets simplified to speed up training
- Performance suffers



## Deployment phase

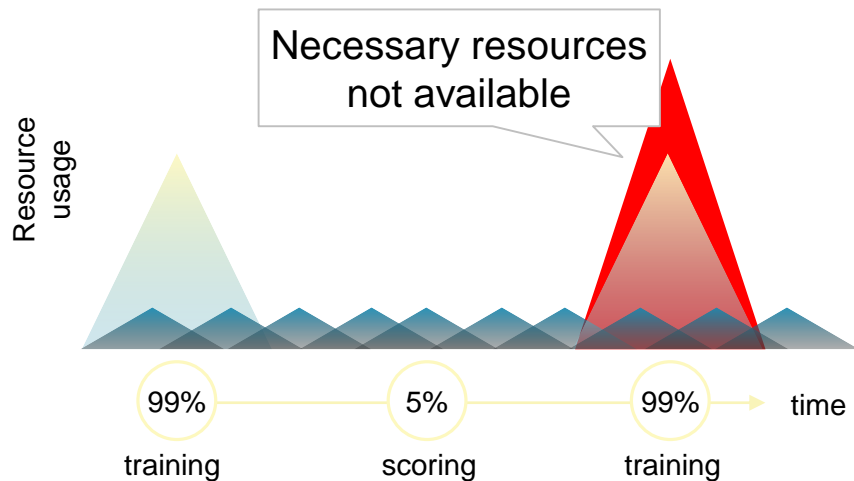
- Dev != Prod
- Server procurement slow
- Server not powerful enough for training
- Server too powerful for scoring



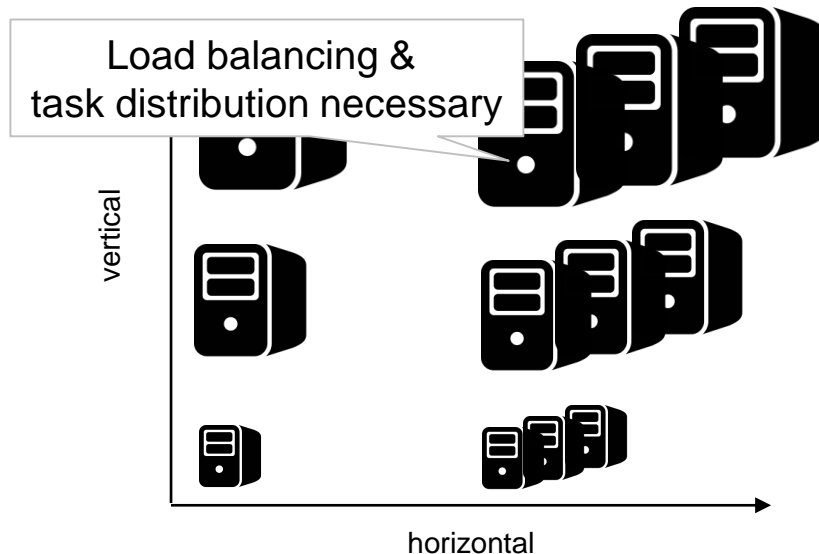
# PROBLEMS WE ENCOUNTERED

## SCALING COMPUTE RESOURCES ON DEMAND

### Resource utilisation



### Scaling options



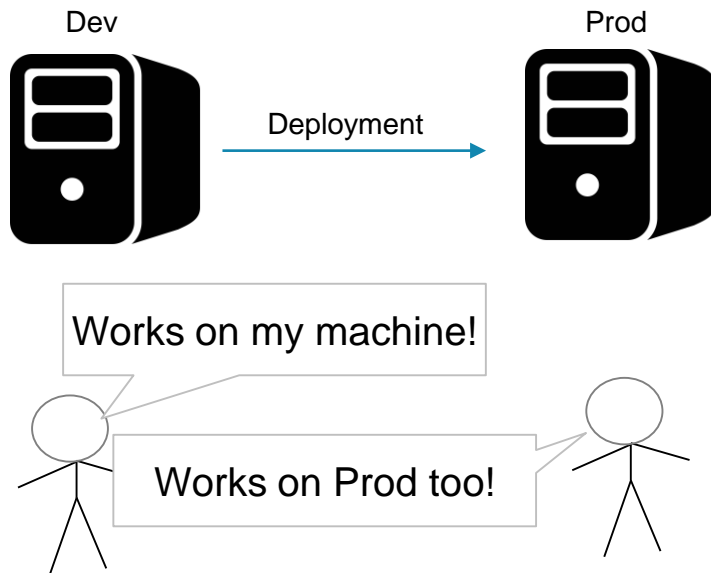
► We want to be able to elastically scale **up** and **out** to meet our needs



# DEPLOYMENT WAS A PAIN ...

## DEV-PROD DISPARITY

### Happy Path Deployments



### Happy Path Deployments



► Keeping Dev and Prod aligned is hard even with best intentions



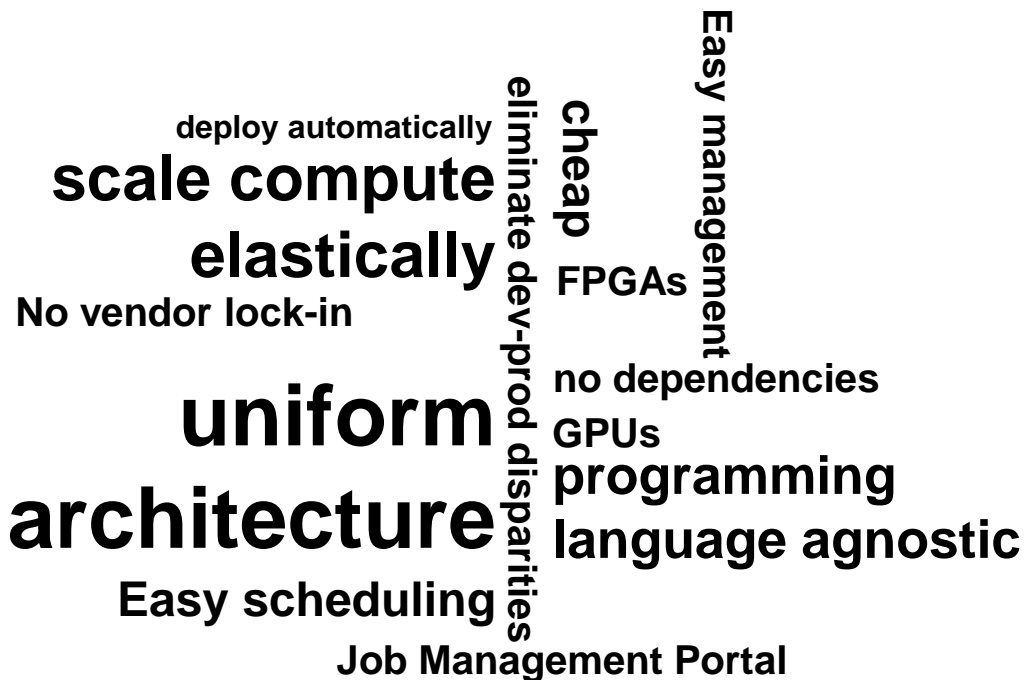
How can we fix these problems?



# HOW CAN WE SOLVE OUR PROBLEMS?

## WE HAVE A LONG WISH LIST

Our wish list:



A word cloud of requirements for solving problems. The words are arranged in a circular pattern, with 'uniform architecture' and 'scale compute elastically' being the largest. Other words include 'cheap', 'FPGAs', 'no dependencies', 'GPU', 'programming', 'language agnostic', 'Easy management', 'eliminate dev-prod disparities', 'Easy scheduling', 'Job Management Portal', 'No vendor lock-in', and 'deploy automatically'.

uniform architecture

scale compute elastically

cheap

FPGAs

no dependencies

GPU

programming

language agnostic

Easy management

eliminate dev-prod disparities

Easy scheduling

Job Management Portal

No vendor lock-in

deploy automatically

Solutions we considered:

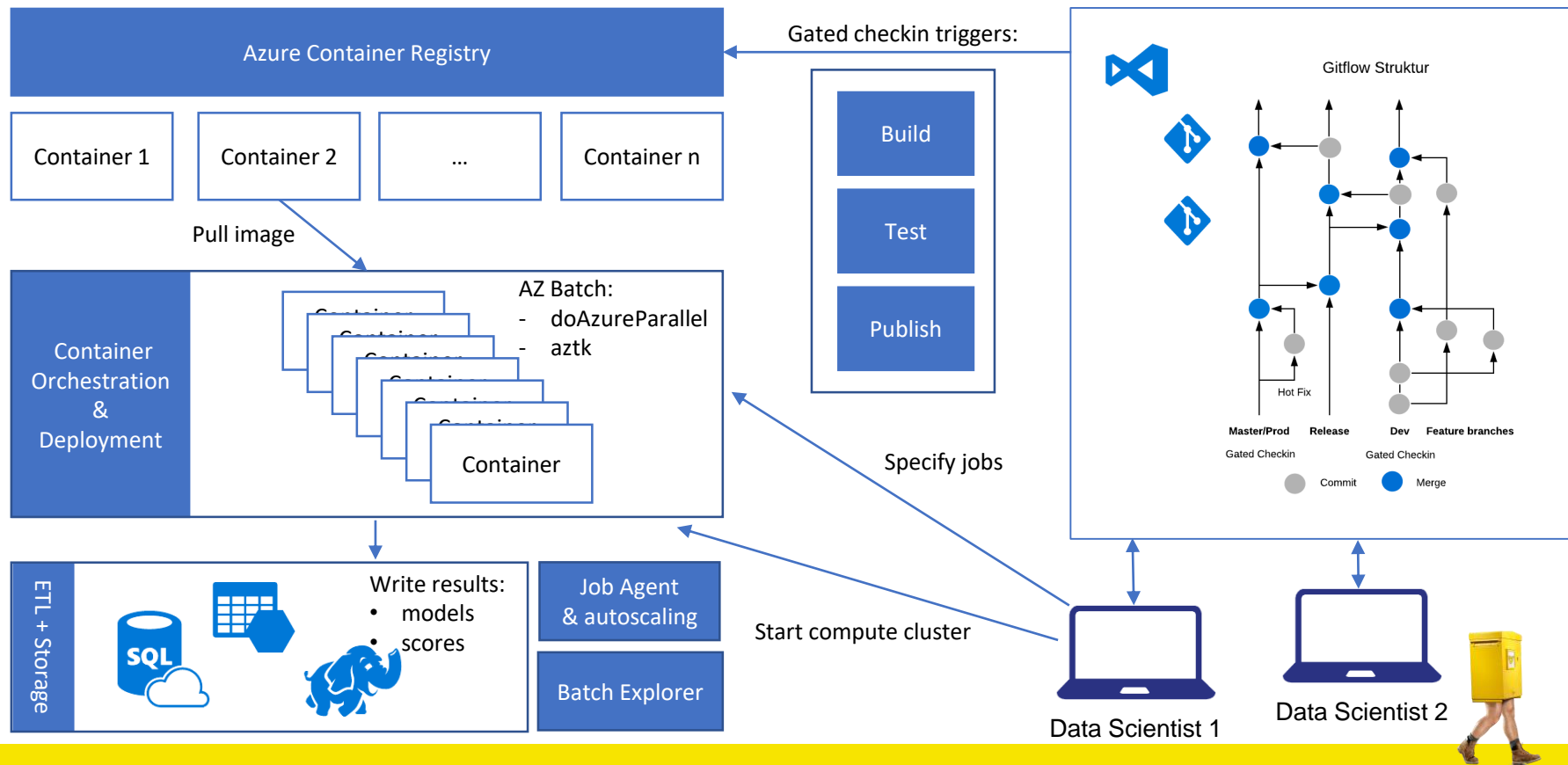
We have two dominant stacks:

- Microsoft .net + Azure
- SAP

Since we have SAP and .net/Azure support in-house, we looked primarily at these two stacks.







# SCALE R WITH AZURE BATCH DEVELOPMENT & PRODUCTION WORKLOADS



# SOLUTIONS WE CONSIDERED COMPARISON

Also take a look at  
Azure Databricks for  
Spark workloads

## Cloud vs. On-Premise Solution

	Azure ML Studio	Azure ML Workbench	Azure Batch	SAP HANA (PAL)
Supported Languages	R/Python	Python	All	R (Python)
Supports GPUs	This looks very promising	Yes	Yes	No
Dev-Prod parity	Easy	Easy	Easy	Hardish
R package available	AzureML	-	doAzureParallel	-
Independent upgrades	partially	partially	Yes	partially
Elastic scaling	-	Yes	Yes	No
Scheduling included	No	No	Yes	Yes
<b>SCORE</b>				





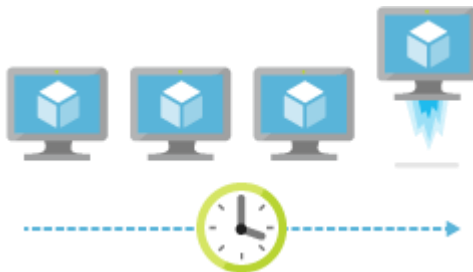
# AZURE BATCH OVERALL WINNER

## FLEXIBLE, HIGH VALUE/MONEY AND LOW VENDOR LOCK-IN



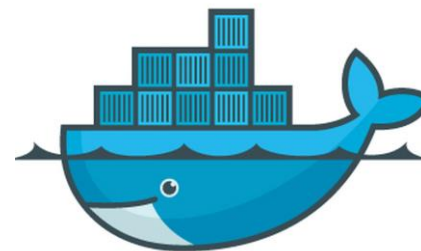
### Scale up and out

Specify node sizes and types, e.g. GPU/CPU, RAM and get large discount on low-prio nodes



### Scheduling integrated

Specify job schedule and resize pool based on number of outstanding tasks



### Docker support

Dev and Prod parity  
Fits into CD pipeline



# DOCKER BRIEFLY EXPLAINED

## BUILD ONCE – RUN ANYWHERE

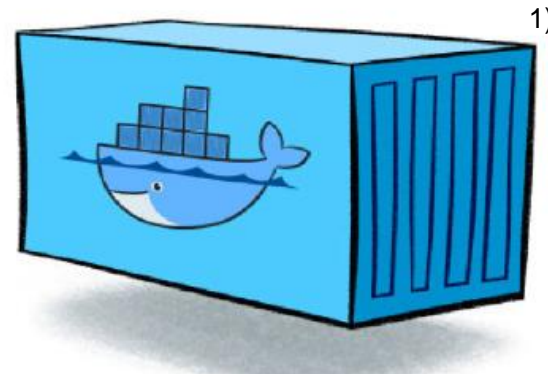
### Example Dockerfile

```
1  ## Description: https://hub.docker.com/r/rocker/tidyverse/
2  FROM rocker/tidyverse
3
4  # Install your R package
5  ## Copy R package to docker
6  RUN mkdir -p /usr/r_package
7  COPY . /usr/r_package
8
9  ## Install package dependencies
10 RUN R CMD SHLIB /usr/r_package
11 ## Roxygenize
12 RUN R CMD SHLIB /usr/r_package
13 ## Install package
14 RUN R CMD INSTALL /usr/r_package
```

R image used

Here we install our package

### Build Container

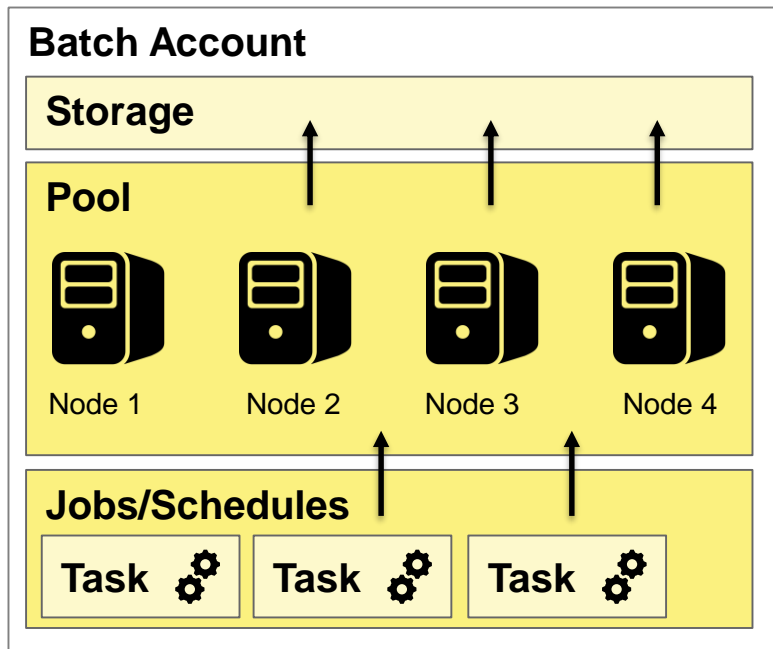


► Container can be deployed to docker runtime in production: Dev = Prod (mostly☺)

Source image: 1) <https://stephenafamo.com/blog/understanding-docker-containers/>



## Components overview



## Description

**Pool** ..... Definition of compute resources

- Node number/type
- Container settings
- Autoscaling
- Task number per node

**Schedule** ... Recurring job for a pool

- Job specification

**Job** ..... Contains pool and task specs

- Job manager task

**Task** ..... Work specification

- Command line
- upload options



# AZURE BATCH SETUP OVERVIEW

## Pool configuration

```
1 # setup batch pool
2 def create_pool(batch_service_client, pool_id)
3     image_ref_to_use = batch.models.ImageReference(
4         publisher='microsoft-azure-batch',
5         offer='ubuntu-server-container',
6         sku='16-04-lts',
7         version='latest'
8     )
9
10    # Private docker repo specification
11    container_conf = batch.models.ContainerConfiguration(
12        ...
13    )
14
15    # create pool specs with pre-fetched images
16    new_pool = batch.models.PoolAddParameter(
17        id=pool_id,
18        virtual_machine_configuration=batch.models.VirtualMachineConfiguration(
19            image_reference=image_ref_to_use,
20            container_configuration=container_conf,
21            node_agent_sku_id='batch.node.ubuntu 16.04',
22            vm_size=_POOL_VM_SIZE,
23            max_tasks_per_node=_MAX_TASKS_PER_NODE
24            enable_auto_scale=True,
25            auto_scale_evaluation_interval='PT5M',
26            auto_scale_formula= "some formula for node type and count"
27        )
28
29    # submit pool creation to azure batch
30    batch_service_client.pool.add(new_pool)
31
```

Pool base image

Here using  
Python SDK

Docker image  
& autoscaling

## Job Manager Task

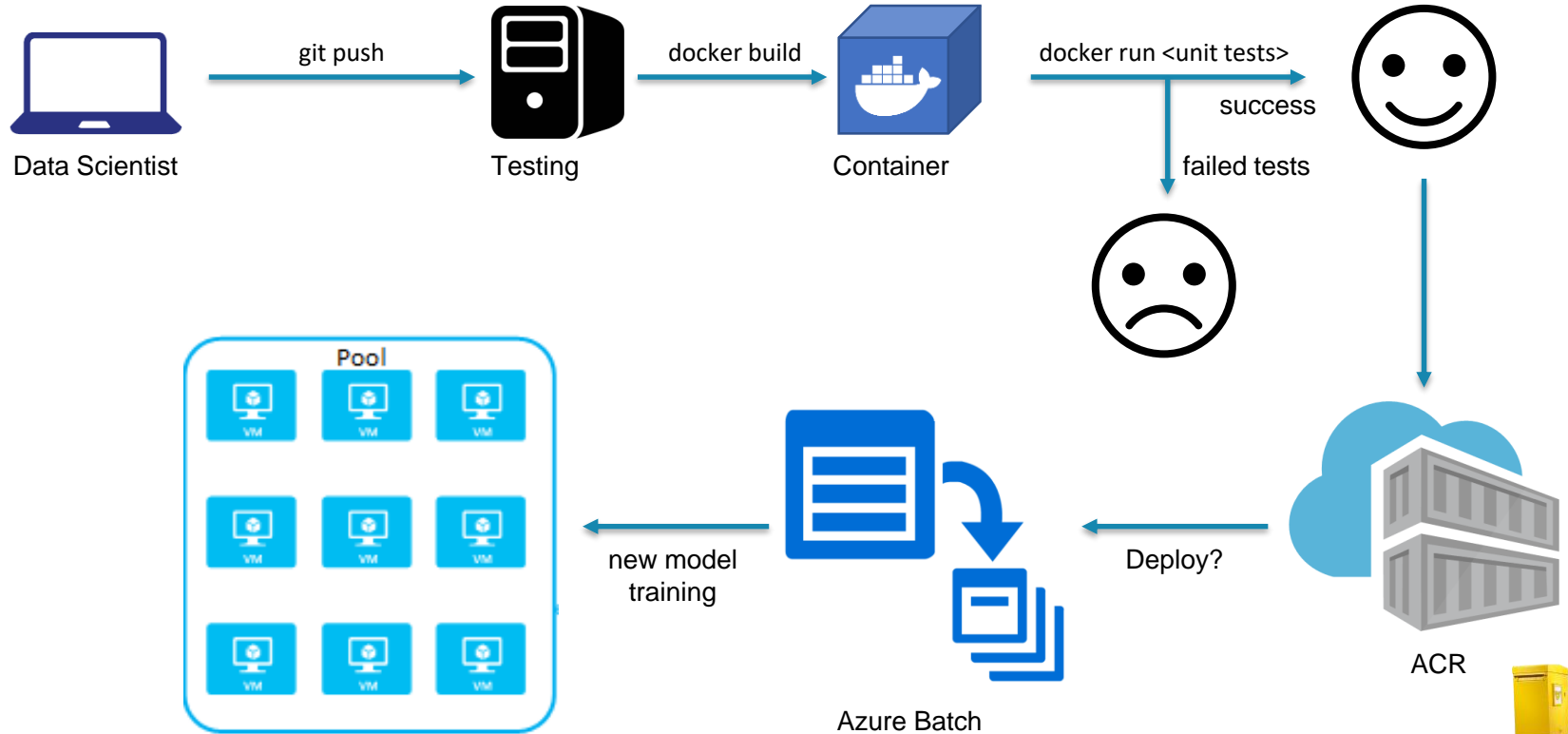
```
33 job_manager = batchmodels.JobManagerTask(
34     id=_AZ_JOB_MANAGER_ID,
35     command_line=_JOB_MANAGER_CMD,
36     container_settings=batch.models.ContainerSettings(
37         authentication_token_settings=batch.models.AuthenticationTokenSettings(
38             access=[batchmodels.AccessScope(
39                 ...
40             )],
41             environment_settings=[
42                 ...
43             ]
44         ),
45         kill_job_on_completion=True,
46         run_exclusive=False
47     )
48
49 job_spec = batchmodels.JobSpecification(
50     pool_info=batchmodels.PoolInformation(pool_id=_POOL_ID),
51     display_name='test_schedule',
52     #on_all_tasks_completion='noaction',
53     job_manager_task=job_manager,
54     #common_environment_settings=None
55 )
56
57 schedule = batchmodels.Schedule(
58     recurrence_interval='PT1M'
59 )
60
61 job_schedule = batchmodels.JobScheduleAddParameter(
62     id=_JOB_SCHEDULE_ID,
63     schedule=schedule,
64     job_specification=job_spec
65 )
66
67 # submit job schedule creation
68 batch_client.job_schedule.add(job_schedule)
```

Command to run

Job schedule  
bundles everything

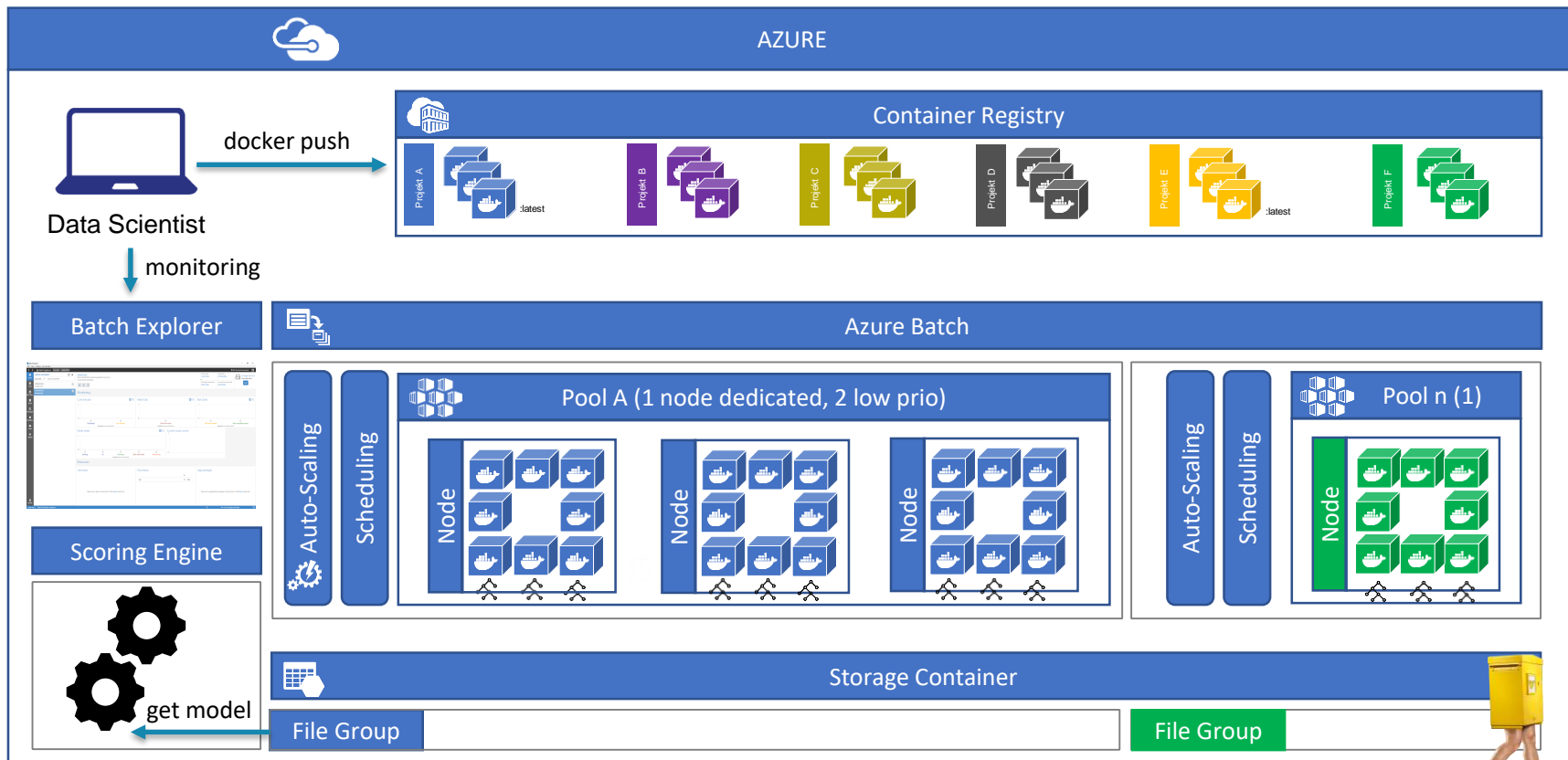


## CONTINUOUS DELIVERY PIPELINE (SIMPLIFIED)

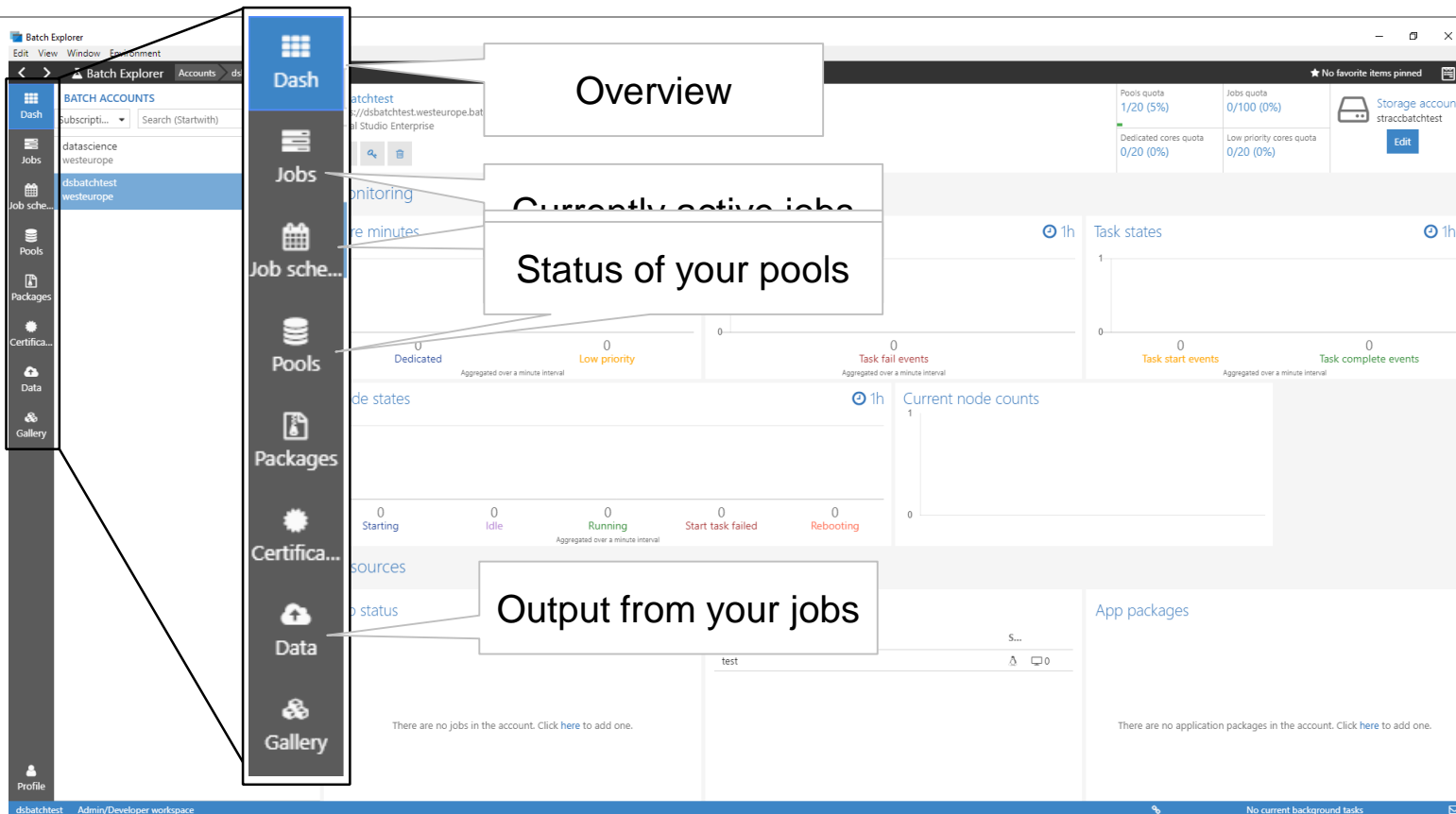


# OUR STACK

## WE ARE CURRENTLY BUILDING A HPC ENVIRONMENT



# MONITORING BATCH JOBS WITH BATCH EXPLORER



The screenshot shows the Batch Explorer web interface. A vertical sidebar on the left contains icons for Dash, Jobs, Job scheduler, Pools, Packages, Certificates, Data, and Gallery. The main dashboard area is divided into several sections:

- Overview**: A callout box pointing to the top of the dashboard.
- Currently active jobs**: A callout box pointing to the 'Jobs' section in the sidebar.
- Status of your pools**: A callout box pointing to the 'Pools' section in the sidebar.
- Output from your jobs**: A callout box pointing to the 'Data' section in the sidebar.

The dashboard content includes:

- Top right**: Quota information for Pools (1/20 (5%)), Jobs (0/100 (0%)), Dedicated cores (0/20 (0%)), and Low priority cores (0/20 (0%)). A 'Storage account' section shows 'straccbatchtest' with an 'Edit' button.
- Task states**: A chart showing task states over a 1-hour period. The y-axis ranges from 0 to 1. The x-axis shows 'Task start events' and 'Task complete events'.
- Current node counts**: A chart showing current node counts over a 1-hour period. The y-axis ranges from 0 to 1. The x-axis shows 'Starting', 'Idle', 'Running', 'Start task failed', and 'Rebooting'.
- App packages**: A section showing application packages.
- Footer**: A blue bar at the bottom with the text 'dsbatchtest Admin/Developer workspace' and 'No current background tasks'.



## 01

## 02

## 03

### Topics

#### Who we are

(obligatory marketing stuff...)

Data Science@Post AG:

- Overview: Post AG
- Our team

#### Scaling R with Azure

Using:

- AzureBatch and
- Docker

for development & production

#### Case study

doAzureParallel + Caret:

- Distributed ML
- Easy setup





## SECURITY & EVALUATING DIFFERENT REAL-TIME SCORING OPTIONS

### Security

- ~~Secret management with KeyVault~~
- ~~Azure Active Directory integration~~
- ~~VNET integration of pools~~
- Docker security best practices audit/check
- Disable public endpoints

What we are currently looking into

### Real-time scoring options

- Using AzureML Studio
- Using Azure Model Management
- Kubernetes Cluster
- Azure Functions
- Azure Container Instances + Logic Apps
- ...



A bit of work is still open, but we plan to have everything wrapped up end of September



# Case Study: Caret + Azure



# LET'S DO A QUICK CASE STUDY

## CARET + DOAZUREPARALLEL

What we will show you:

- How to setup a Batch Account in Azure
  - Things to consider: VNET, AAD, region...
- Download BatchExplorer
- Get credentials
- Switch to R:
  - Using a custom Docker image
  - Train models in parallel using caret+doAzureParallel as backend



## AZUREBATCH OFFERS EFFICIENT AND FLEXIBLE HPC

### Development

- Use doAzureParallel to test multiple models quickly
- Create Docker container for your colleagues to use
- Push to container registry

### Production

- Use container image from development
- Setup schedule and cluster specification
- Configure autoscaling and
- Violá 😊

▶ You get a cost efficient, flexible and scalable architecture for your team



Thank you for  
your attention!

Any questions?



You can contact us at:

- [linkedin.com/in/christoph-bodner](https://www.linkedin.com/in/christoph-bodner)
- [linkedin.com/in/thomas-laber/](https://www.linkedin.com/in/thomas-laber/)

