

Operational Intelligence

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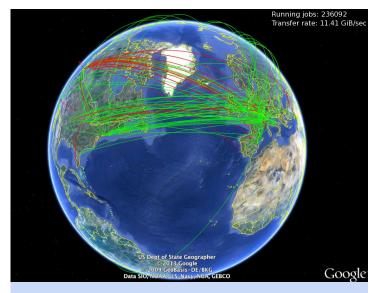
Federica Legger

on behalf of the Operational Intelligence forum

- A **cross-experiment** effort aiming to streamline computing operations:
 - Minimize human effort in operations by increasing **automation**
 - **Improve resource utilization** by reducing wasted cycles
 - **Build a community** of technical experts: critical mass to have impact
- Our mission:
 - Identify **common projects**
 - Leverage common tools/infrastructure
 - **Collaborate**, share expertise, tools & approaches
 - <u>Across experiments</u>
 - <u>Across teams</u> (operations, monitoring, developers)

WLCG - Worldwide LHC computing grid

- Distributed computing infrastructure that provides computing services and storage resources to process and store LHC data
- WLCG is made of 900 000 computer cores from over 170 sites in 42 countries
- WLCG runs over 2 million tasks per day and, by the end of LHC Run 2, global transfer rates regularly exceeded 60 GB/s
- Close to an exabyte of LHC data already collected and stored



- Distributed workload management (WM)
- Distributed data management (DM)
- Sites and facilities

Preparing for High Lumi LHC

- LHC experiments built successful computing systems for LHC Run 1/2
 - We do not have a simulation of the Grid
 - Up to now we monitored to debug in near-time.
 - Can we do better?
- HL-LHC: one order of magnitude more resources than today
 - Personpower will not scale
- **However**: computing operations (meta-)data is all archived
 - We have logs for transfers, job submissions, site performances, infrastructure and service behaviours, storage access
 - All this knowledge should be exploited!



• Run an **experiment-agnostic technical forum** to:

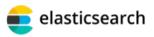
- Bring people together
- Discuss ideas, brainstorm, share experience and code
- We identified areas where shared development can occur:
 - Workflow Management
 - Data Management
 - Computing facilities
- We provide some **shared infrastructure**:
 - A common k8s cluster for services to be deployed.
 - A framework which can be used to develop new tools

ML areas of interest

- **Classification**: predict which transfers/jobs will fail
 - Decision trees, neural networks, ...
- **Regression:** predict time-to-complete for jobs, transfers, campaigns
- **Clusterization**: group alerts, errors, root cause analysis
 - K-means, DBscan, PCA, ...
- Natural Language Processing (NLP): log text analysis, tickets
 - Word2vec, transformers, ...
- Anomaly detection: detect problematic links, hosts, storage end-points
 - Time series, multi-variate, ...

Infrastructure





- Based on **open-source** products
 - Kubernetes for **deploying and scaling services**
 - HTTP and AMQ for data injection
 - Prometheus and ElasticSearch for **managing**

metrics and meta-data

- Features:
 - Clear separation of Data, Infrastructure, Visualization
 - Data standardization, common naming convention, data validation
- Automation:
 - Data annotation, alerting, notifications, tagging

















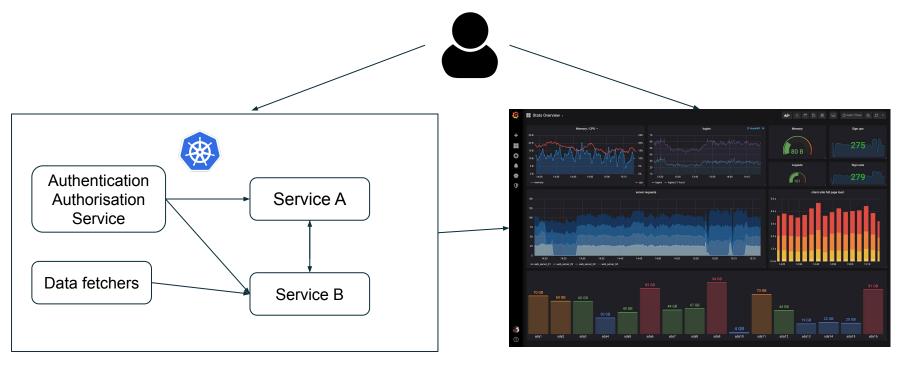




The shared k8s cluster

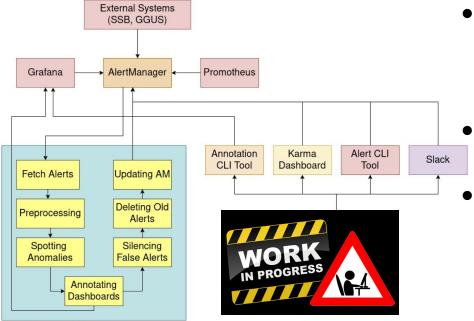


common (not experiment specific) space to deploy applications



Intelligent Alert system

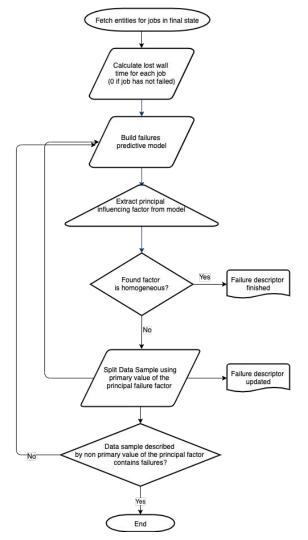
• We added an intelligent layer to CMS monitoring infrastructure to **detect**, **analyze and predict abnormal system behaviors** using **alerts**



- The alert manager fetches the existing alerts, filters them, and **annotates** Grafana dashboards based on the alert tag
- SSB and GGUS are also integrated into the Alert Manager
- The system provides useful insights about when outages happen and how they affect the productivity reported by various systems in CMS dashboards

Workload management: Jobs Buster

- ATLAS " Jobs Buster" tries to spot
 operational problems in submitted jobs
- Uses catboost library
 - Naturally supports both categorical and numerical features (walltime, CPU time, pilot version, software version, error message, site)
 - Supports GPU and CPU

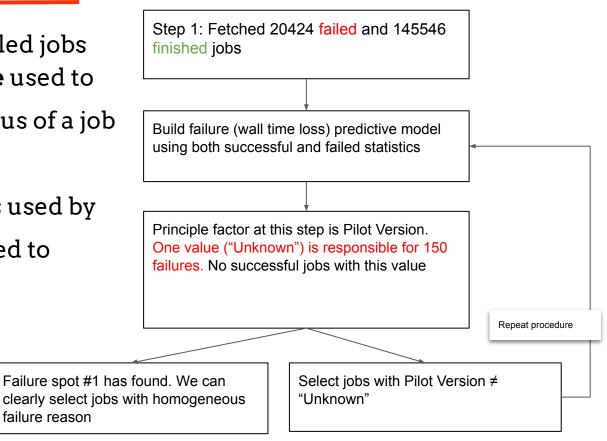


Predictive model

- Input: successful and failed jobs
- **Gradient Boosting Tree** used to predict the outcome status of a job by its features
- Most important features used by GBTs are ranked and used to extract the root cause

failure reason

Iterative procedure



Results



Data Management - FTS

FTS (FileTransferService) is the service responsible for globally distributing the multiple petabytes of LHC data across the WLCG infrastructure.



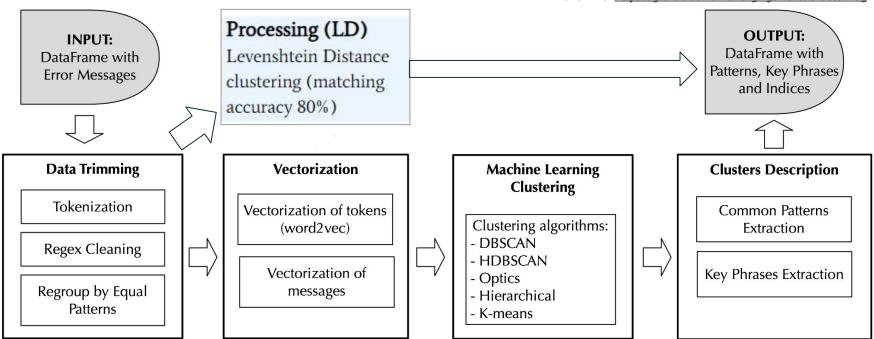
~10^5-10^6 error messages per day

Analysis of FTS error messages

- Every day operation teams must deal with multiple data transfer errors
- The monitoring systems help users to detect anomalies, to identify duplicated issues, to diagnose failures and to analyze failures retrospectively
- Clustering of error messages is a possible way to simplify the analysis:
 - Messages having the similar text pattern and error conditions are grouped
 - Groups of similar messages are described by the common text pattern(s) and keywords
 - Messages encountered only once or several times are considered as anomalies
- There are currently multiple efforts trying to analyze the error messages and simplify operations

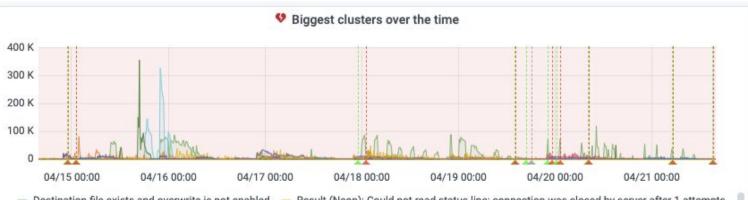


• ClusterLogs is a framework developed within OI to cluster error messages



More info: <u>https://github.com/maria-grigorieva/ClusterLog</u>

CMS FTS log analysis with LD



— Destination file exists and overwrite is not enabled — Result (Neon): Could not read status line: connection was closed by server after 1 attempts

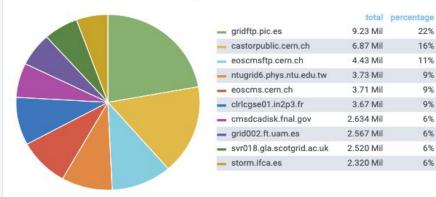
globus_ftp_client: the server responded with an error 421 The GridFTP Service is busy and unable to accept this connection. Please try again later.

Error reported from srm_ifce : 2 [SE][Ls][SRM_INVALID_PATH] No such file or directory

— [gfal2_stat][gfal_plugin_statG][davix2gliberr] Result HTTP 404 : File not found after 1 attempts — F

ClusterLogs is used to classify File Transfer Service (FTS) logs and results pushed back to the MONIT infrastructure where they can be browsed from a Grafana dashboard

More info: <u>http://cern.ch/go/qk7S</u>

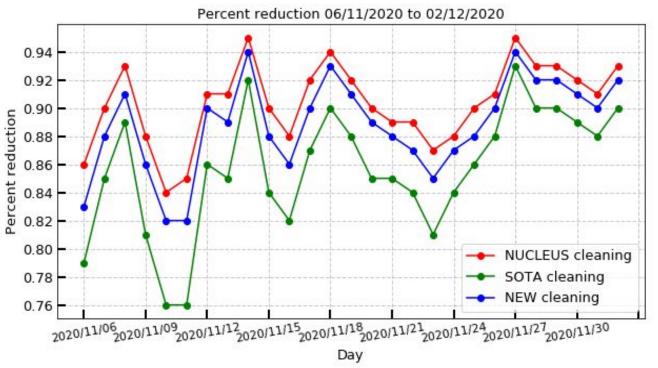


Most failing destination hostnames

CMS FTS log analysis with ML vs LD



- ML model (Word2vec+DBsca n) requires more cleaning than LD approach
- Less clusters with ML, but top 10 clusters basically the same
 - Difference of
 1-2 clusters/day



Clustering FTS Errors - Method



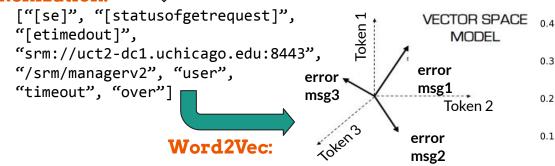
Vectorization (offline)

- Transform textual information into numerical
- Minimal pre-processing (split URLs and remove punctuation)

Raw message:

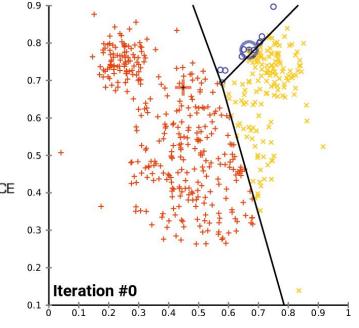
```
[se][statusofgetrequest][etimedout]
srm://uct2-dc1.uchicago.edu:8443/sr
m/managerv2: user timeout over.
```

Tokenization:



Clustering (online - daily)

 Group message vectors using KMeans algorithm

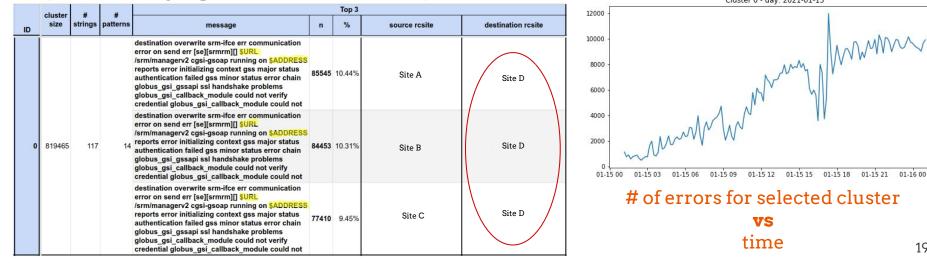


Clustering FTS Errors - Results



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- Main results are: i) summary table and ii) time evolution plot **Highlights**:
 - Clusters contain similar messages, although allowing some variability
 - The model learns to abstract message parameters as IPs, URLs, file paths
 - Evolution plots give immediate indications on errors time trends (increasing, cyclical, transient, ...) Cluster 0 - day: 2021-01-15



Clustering FTS Errors - Validation



- Clustering results compared to GGUS tickets opened within ± 3 days from the period of the analysis (15 January 2021)
- Promising results :
 - **Exact match:** GGUS site *AND* message match cluster summary
 - **Fuzzy match:** evident connection with more than one ticket
 - **Partial match:** GGUS site *OR* message match cluster summary

N. Clusters	Exact	Fuzzy	Partial	False	False	
	Match	Match	Match	Positives	Negatives	
15	7	3	2	3	1	

Highlights:

- Some false positives were real problems, but were not reported in GGUS
- Few false negatives: unusual to have issues completing undetected

Anomaly detection on FTS transfers

- Ongoing collaboration with **Google** and **UCL** to develop a recommendation system to prioritise transfer errors
- Analysis of FTS data showed that we can study errors evolution not only over time but also over the interconnection between nodes (links)

									dst /	Record Count
src	s/m-cms.gri	gridftp.swt_	dtn.ilifu.ac.za	gridftp.hep	t2cmcondo	tbn18.nikhe	uct2-dc1.uc	fal-pygrid-3_	griddev03.s	bohr3226.ti
bohr3226.tier_	(5,739	737,095	(34)	6,911	19,902	3,490	10,940	55,722	136
tbn18.nikhef.nl		12,891			14,466		6,133	14,429	893	14,515
eoscmsftp.ce_	38,806	्र		37,524		12	10	1.5	1.00	
dcsrm.usatla		63,813			44,551	8,058	19,459	14,912	(H)	4,844
uct2-dc1.uchi_		4,764			3,487	7,157	45	6,938		28,582
eosatlassftp	374	39,750	5.	1	65,132	10,828	33,056	11,091	100	1,908
ccsrm.in2p3.fr	32,366	43,079		23,902	31,446	2,875	5,364	4,988	(2)	1,177
golias100.far_	(a.)	5,196			1,397	18,766	1,973	10,772	61,104	10,434
sdrm.t1.grid.k_		14,670			8,203	16,549	1,018	10,025	874	9,462
storm.ifca.es	13,081			5,582						

Oct 1, 2019 - Nov 1, 2019

Figure 3: Count of errors over connection pairs

MIDAS (MIcrocluster-based Detector of Anomalies in Streams)

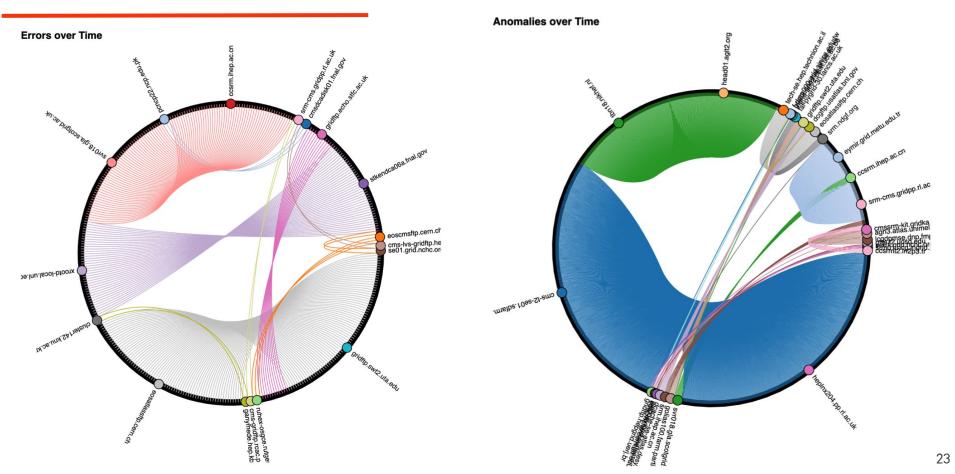
More info: https://arxiv.org/pdf/1911.04464.pdf

- Finds anomalies in dynamic graphs (file transfers, intrusions)
- Detects micro-clusters (sudden "burst" of connections between nodes (multiple retrials, DOS)
- Memory usage constant and independent of graph size
- Update time in streaming scenarios is also constant

									Star	t_Hour / Record	Count
Top 10 - dat	Top 10 - data	201_	Oct 10, 201	Oct 1							
bohr3226.lier_	dtn.ilifu.ac.za	4,106	3,450	3,511	4,215	4,636	3,411	3,155	3,782	4,600	
	griddev03.sla	2	-	-	-	-	-	-			
	serv02.hep.p_	183	163	143	171	207	155	171	210	195	
	tbn18.nikhef.nl	50	55	51	49	43	211	20	7	25	
	fal-pygrid-30.1	32	38	34	29	27	25	14	26	62	
	f-dpm000.gri_	27	32	26	28	25	398	3	2	5	
	ftp1.ndgf.org	26	29	26	28	23	395	3			
	sdrm.t1.grid.k	25	28	27	28	25	201	3	10		
	dcache-atlas	26	29	26	26	26	323	3			
	srootd.echo.s	23	29	29	26	21	202				

Figure 4: Variation over time for a given connection pair

Results



Anomaly detection on transfers



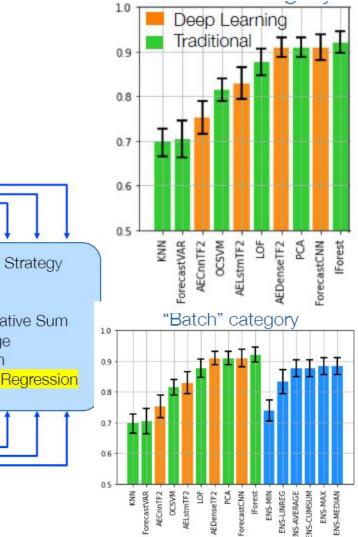
- Next steps:
 - Include text features in anomaly detection. We must consider not only the number, timing and location of links between nodes, but also the messages.
 Other metadata such as user, file size etc... may play a role too
 - Include data from GGUS tickets to validate the results
 - Build an interface for shifters to explore the results of this analysis
- This effort is now a pilot project in the EU CloudBank: <u>https://ngiatlantic.eu/funded-experiments/cloudbank-eu-ngi</u>

Cloud anomaly detection

- A CERN-IT project to detect anomalies in the CERN Cloud:
 - Identify operational issues
 - Get a comprehensive understanding of the cloud performance
- A grafana annotations enhancement has been developed in parallel to:
 - Allow experts easily give feedback on the results, directly from Grafana

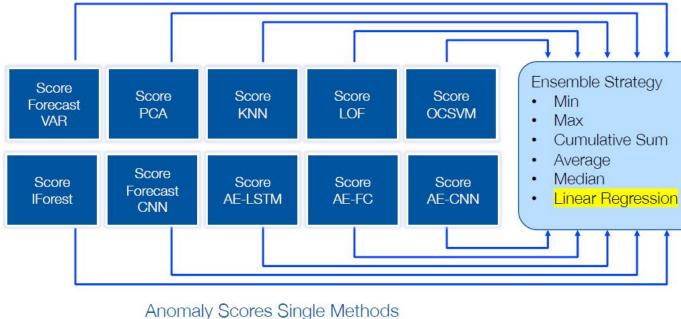


Cloud anomaly detection



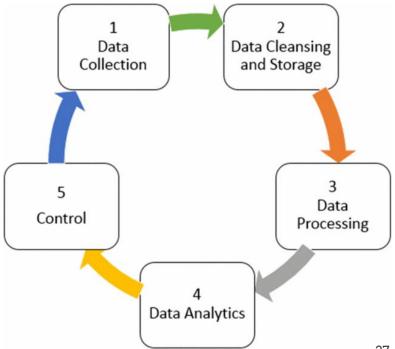
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Facilities: Industry examples

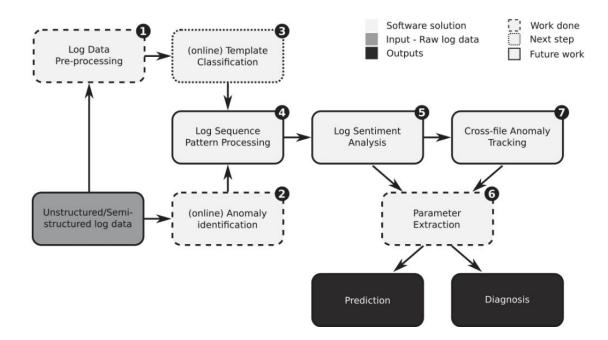
- Building sensors throughout their networks so that they can redirect workload to offload overloaded nodes
- Using SMART (Self-Monitoring, Analysis and Reporting Technology) to derive disk failure predictions and replace hardware proactively
- Using AI to manage the cooling and power management of the data center (advertising up to 5% gains in performance)
- In general: **predictive maintenance** based on sensors and computing logs



INFN Bologna - Predictive maintenance



- From reactive maintenance to predictive maintenance
- Parsing the logs of computing services



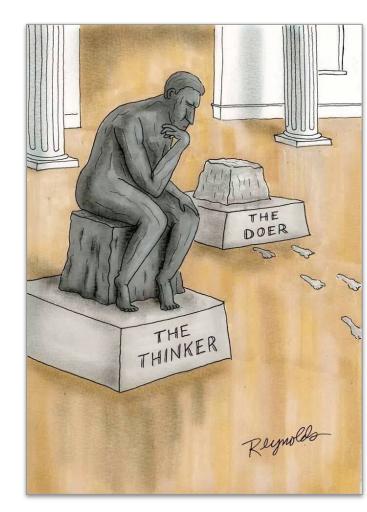


Service	Status				
Intelligent Alert System	In production				
Shared k8s cluster	Work in progress				
Jobs Buster	In production				
HammerCloud JobShaping	In production				
FTS log analysis (Levenshtein distance)	In production				
FTS log analysis with ML	In testing phase				
FTS Anomaly Detection with Google	Work in progress				
Cloud anomaly detection	In production				
INFN Bologna - Predictive Maintenance	Work in progress				

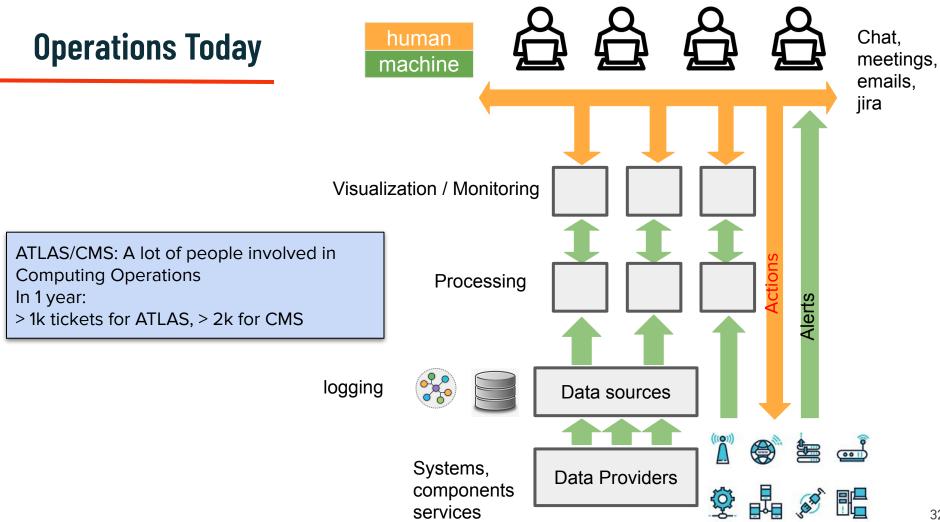
Outlook

- We have in the past 2 years gathered expertise and an understanding of the various efforts
- Lot of opportunities to span new collaborations and work on exciting cross-experiment projects
- Challenges:
 - Anomaly detection/NLP
 - Lack of annotated datasets
 - Deploy to production

operational-intelligence@cern.ch https://operational-intelligence.web.cern.ch/



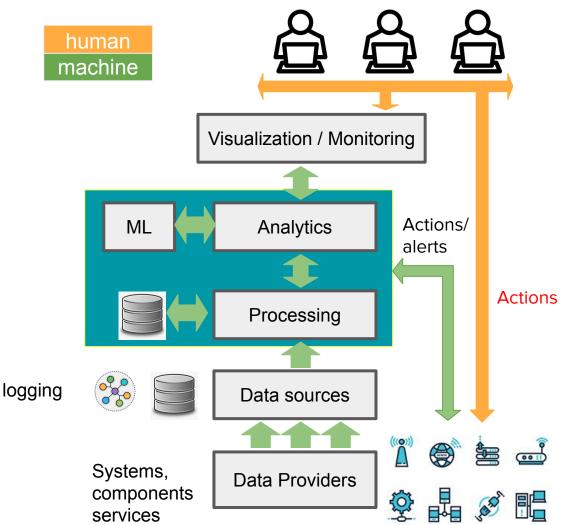






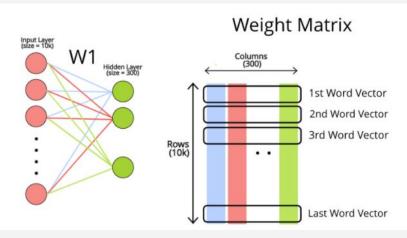
Frontend: aggregated views, suggestions, collects feedback

Backend: Fetches, stores, filters, and analyses information about alerts, issues and solutions

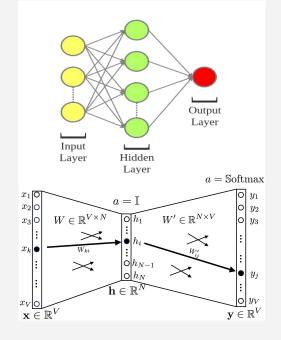


Word2Vec

- Mapping of words into vectors
- Shallow Neural Network (NN): stack of hundred processing units (*neurons*) interconnected by nodes . Processing units are made up of input and output units. Weight to be learnt for each interconnection



(Ref. backup for Hyper-parameters values)



DBSCAN

DBSCAN - Density-Based Spatial Clustering of Applications with Noise

Two parameters, **min_samples and eps**, which define formally the concept of *density* :

- **eps=** maximum distance between two samples for one to be considered as in the neighborhood of the other.
- **min_samples=** number of samples in a neighborhood for a point to be considered as a core point. This includes the point itself.

Higher min_samples or lower eps indicate higher density necessary to form a cluster.

