Bladder Cancer Diagnosis using Deep Learning

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Strata
DATA CONFERENCE

Agenda

- Who We Are
- Bladder Cancer Diagnosis using Deep Learning Study
- Global Enablement for Cancer Study using Big Data and Deep Learning

Dell Technologies Addresses All Four Transformation Pillars

Digital Transformation

IT Transformation

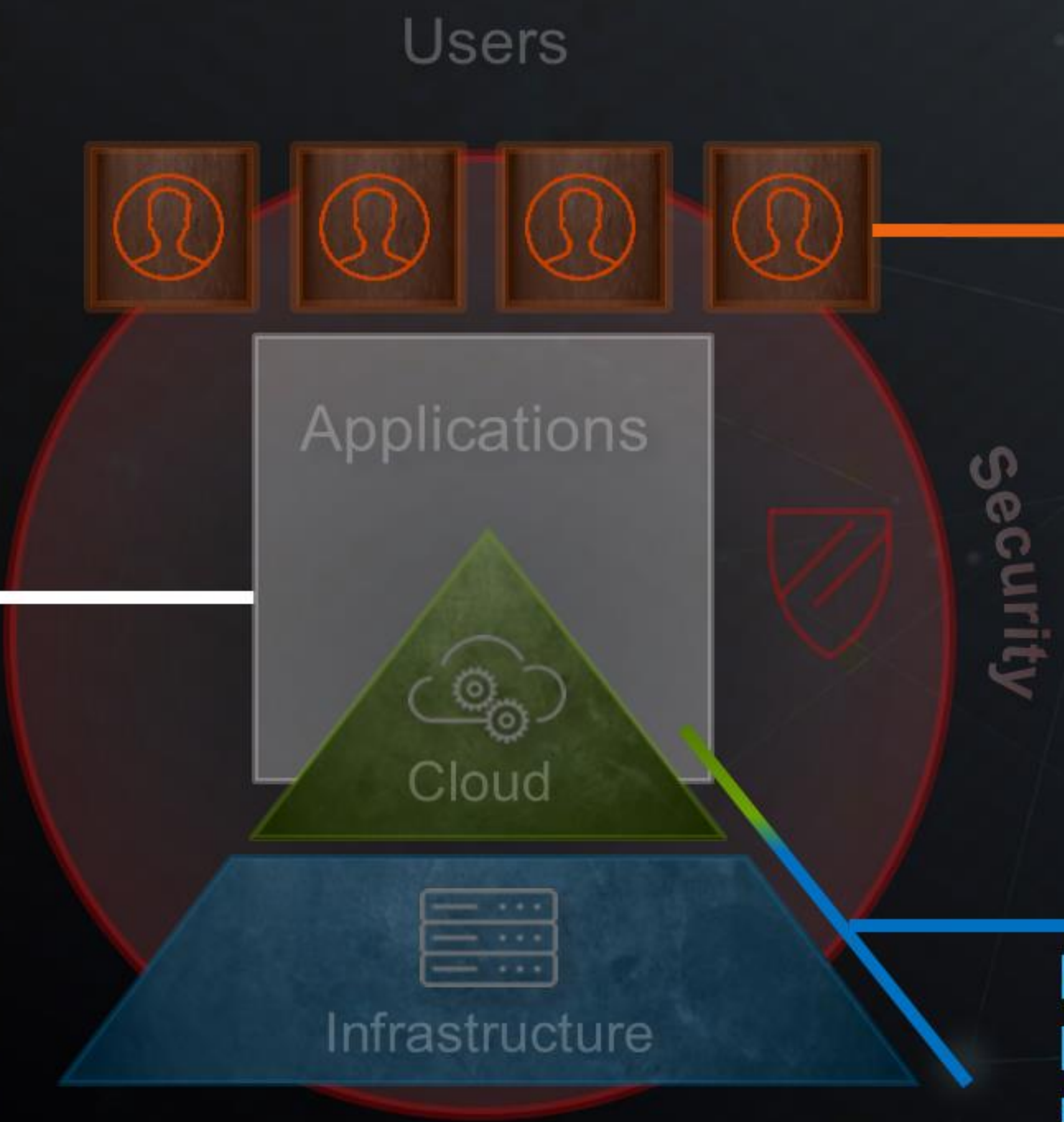
Workforce Transformation

Security Transformation

Dell EMC Consulting

Our expert consultants accelerate time-to-value for our customers' transformations by leveraging our deep knowledge across Dell Technologies

TRANSFORMATIONAL PROGRAM OFFICE



Workforce Transformation

VDI and End User Computing
Digital Workplace Portals
Communication and Collaboration

Digital Transformation

Cloud Native Apps and DevOps
Application Portfolio Optimization
Big Data, IoT, Analytics, and Platforms

IT Transformation

Multi-cloud Infrastructure and Operating Model
Data Center Modernization and Migration
Business Resiliency

PEOPLE ← PROCESS → TECHNOLOGY

Big Data & IoT Consulting Services

Helping customers with their digital transformations

ADVISE

- Data Strategy
- Use Case Prioritization
- Capability Assessment
- Solution Architecture / Design
- IoT Planning
- DaaS Planning and Architecture
- Technology Advisory Services

PLAN

EXECUTE

PROGRAM and Organizational Enablement

- Operating Model (Skills, Org, Process)
- Skillset Assessment
- Governance Integration
- Financial Impact Analysis
- Use Case Development
- Analytics Factory
- Mentorship Program
- Data Science as a Service
- Use Case Operationalization

ANALYTICS from Exploration to Production

- Complex Events Analysis
- Analytical Models Enhancement
- Predictive Analytics
- IoT Analytics
- Machine Learning/Deep Learning
- Text, Audio, Video and Image Analytics
- HPC and GPU Computing

PLATFORM Design, Implementation and Optimization

- Solution Architecture/Design
- PoC, PoV, Tools Validation
- Tech Assessment & Health Check
- ETL/EDW Offload and Migration
- Hadoop Implementation (DAS/NAS)
- Hadoop on Isilon Services

DELL EMC

Bladder Cancer Diagnosis using Deep Learning Study

Bladder Cancer is the fourth most common in men

- **430,000 new cases** per year globally
- Estimate of **81,191 new bladder cancers in US** and **fourth most common** in men
- Direct medical **cost** of bladder cancer care was **$125B** in 2010 globally
- Cost of muscle-invasive bladder cancer is **$150k** and early stage cancer (first 2 yrs) is **$10k per patient** globally

Source:The Economics of Bladder Cancer: Costs and Considerations of Caring for This Disease. obert S. Svatek a , Brent K. Hollenbeck b , Sten Holma¨ng c , Richard Lee d , Simon P. Kim e , Arnulf Stenzl f , Yair Lotan g, *http://www.europeanurology.com/article/S0302-2838(14)00018-9/pdf/the-economics-of-bladder-cancer-costs-and-considerations-of-caring-for-this-disease. 2014
. Bladder Cancer Incidence and Mortality: A Global Overview and Recent Trends. https://www.ncbi.nlm.nih.gov/pubmed/27370177, Antoni S[1], Ferlay J[1], Soerjomataram I[1], Znaor A[1], Jemal A[2], Bray F[3]. 2012
. https://www.cancer.org/research/cancer-facts-statistics/all-cancer-facts-figures/cancer-facts-figures-2018.html

Our Proposal

- Multinomial classification of primary tumor that can recognize bladder cancer in Magnetic Resonance Images without human intervention
- TMN classification
  - **Tumor: How large is the primary tumor? Where is it located?**
  - Node: Has the tumor spread to the lymph nodes?

    If so, where and how many?
  - Metastasis: Has the tumor spread to the lymph nodes?

    If so, where and how many?
- **Focus on primary tumor**
- Tracked 4 different types of primary tumors of bladder cancer: **T2a, T2b, T3a and T4a**

Hardware and Software Stack

Intel Xeon E5-2680 @ 2.7GHz with 8 cores and 384 GB

NVIDIA GRID K2 with 2 GPUs GK104 with 1.536 cores per GPU and 4 GB per gpu RAM

2.7.5

Script Laguage with the following packages. Main data trasformation

Python
Numpy
Matplotib
OS
Jupyter

1.4

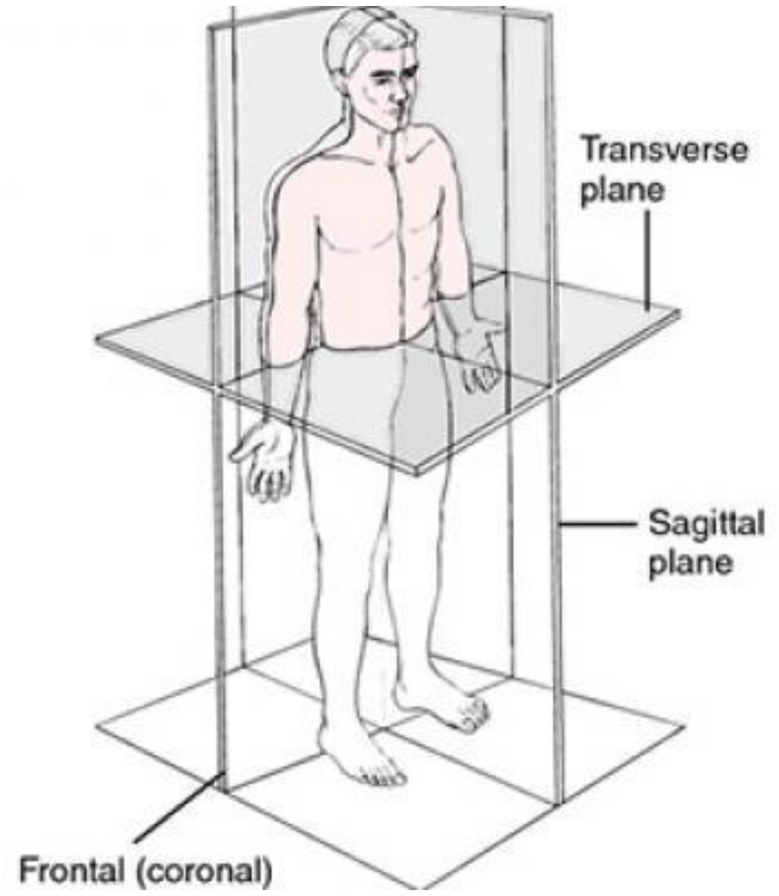
Deep Learning package:
- Neural Network Build and Design
  - Mini batch process
- Functions and Loss Functions
  - Algebra Computation
  - Optimization Process
-

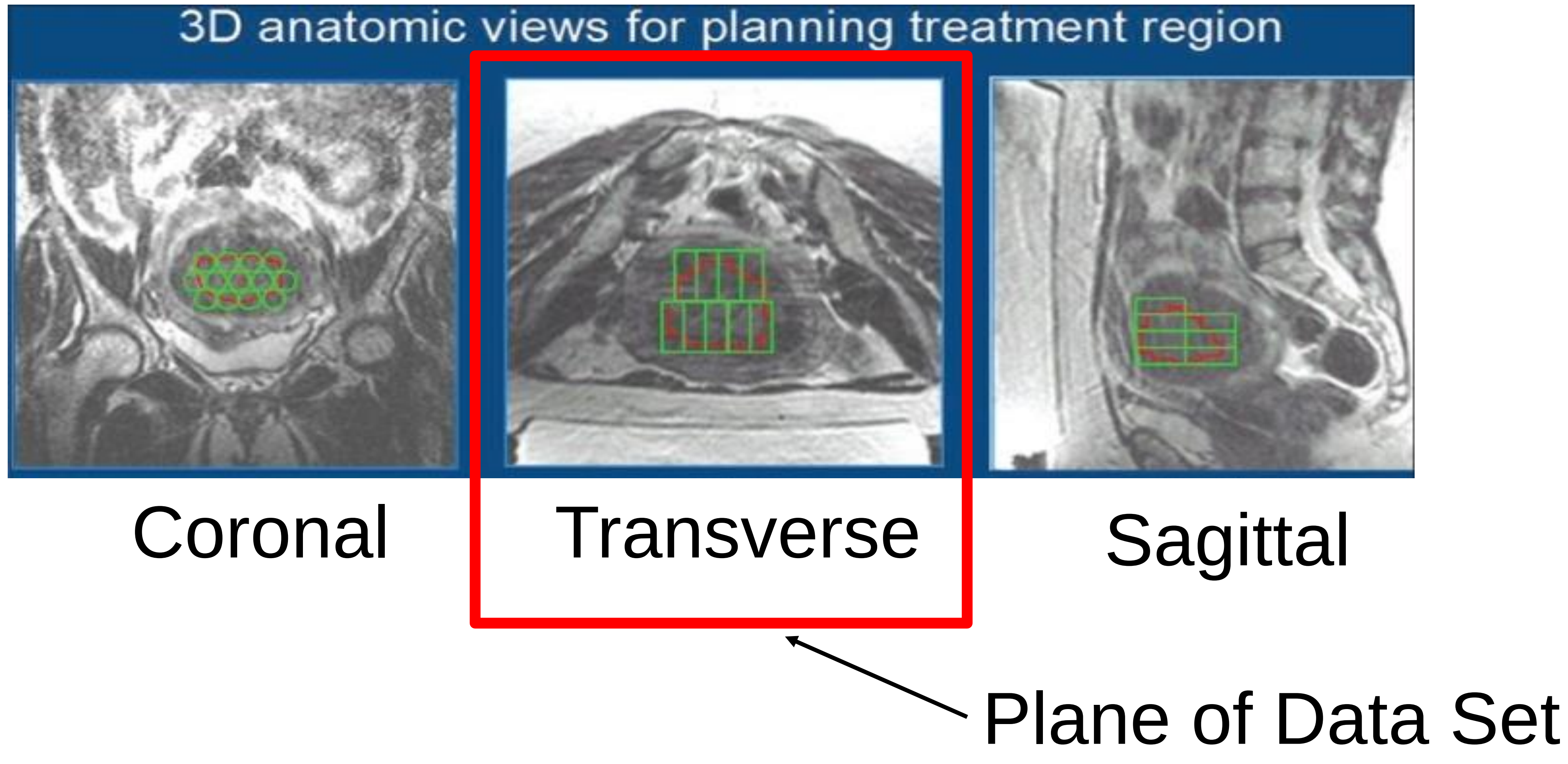
Image transformation package:
- Shrink
- Binarization

Medical Image file standard
Library to access the Metadata and Data (Pixels)

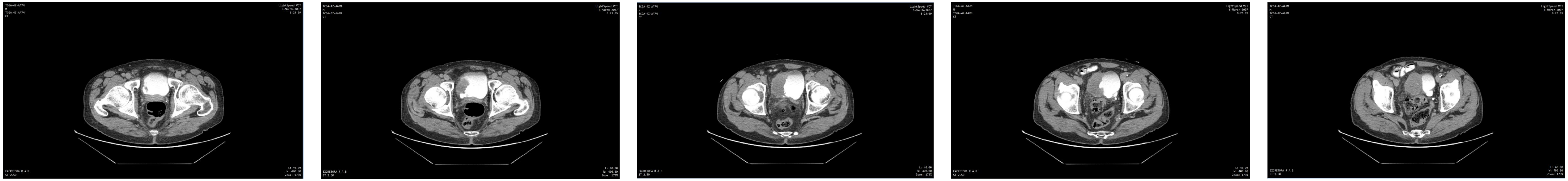
How MRI device scans patient organs

- MRI device can scan the patient in 3 gradients - each of them create an image with a different perspective
  - Coronal
  - Transverse
  - Sagittal





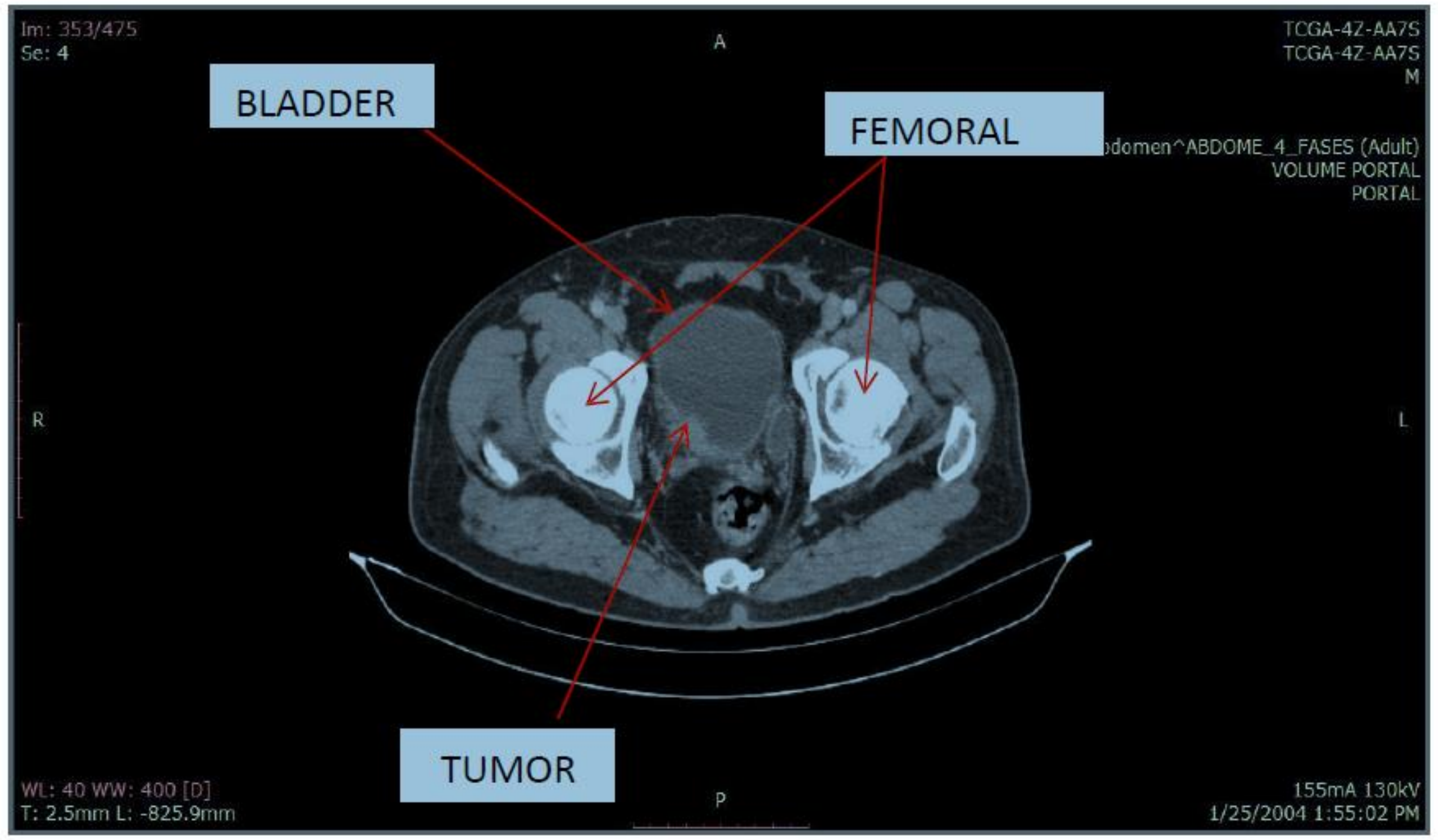
Different angle from the pelvic region



Source: http://www.machinedesign.com/medical/what-s-difference-between-sagittal-coronal-and-transverse-planes
https://www.researchgate.net/figure/Axial-sagittal-and-coronal-T2-weighted-magnetic-resonance-MRI-images-of-the-pelvic_fig1_235423544

Data Set and Images

- 5,019 Magnetic Resonance Images of the pelvic region from patients
- No previous image selection for all the images in the session
- No image cropping or regional detection was done in raw data
- All patients had cancer - our goal was to detect the class of the tumor in different patients



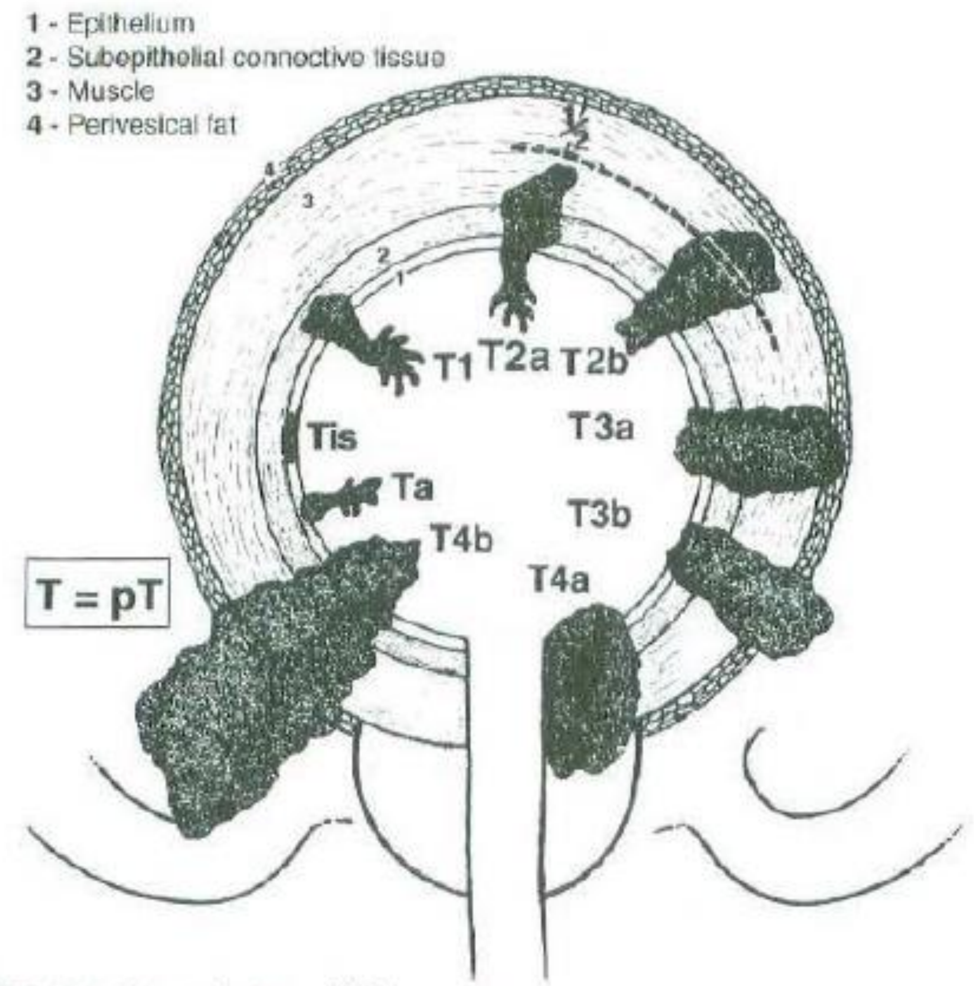


FIG. 38.1. Extent of primary bladder cancer.

Figure 6 - Extent of primary bladder cancer

Primary Tumor (T)

TX	Primary tumor cannot be assessed
T0	No evidence of primary tumor
Ta	Non-invasive papillary carcinoma
Tis	Carcinoma *in situ:* "flat tumor"
T1	Tumor invades subepithelial connective tissue
T2	Tumor invades muscle
pT2a	Tumor invades superficial muscle (inner half)
pT2b	Tumor invades deep muscle (outer half)
T3	Tumor invades perivesical tissue
pT3a	microscopically
pT3b	macroscopically (extravesical mass)
T4	Tumor invades any of the following: prostate, uterus, vagina, pelvic wall, abdominal wall
T4a	Tumor invades prostate, uterus, vagina
T4b	Tumor invades pelvic wall, abdominal wall

Data Transformation and Tensors

MRI IMAGES
Gray Scale
512x512

→ Shrink subsample →

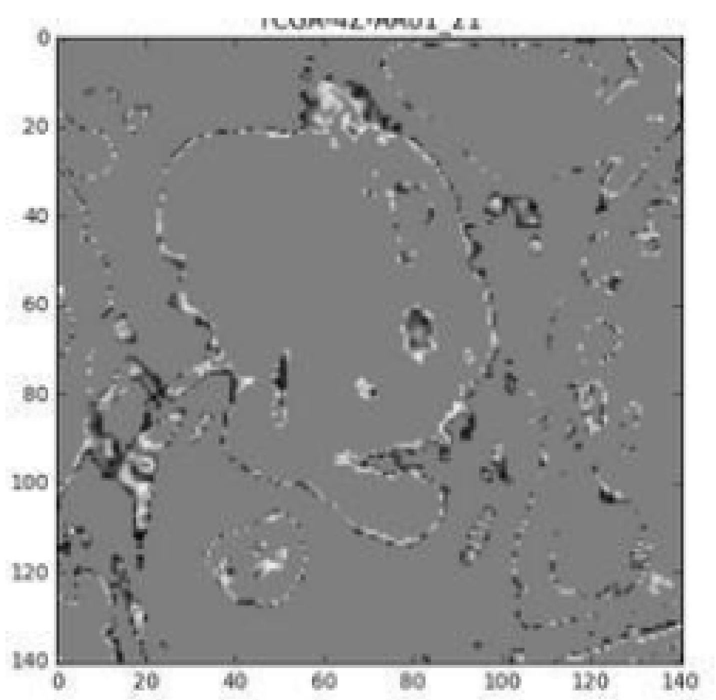
MRI IMAGES
Gray Scale
256x256

→ Threshold PIxels →

Transformed
MRI IMAGES
Binarizarion
256x256

Transform in tensor with (256,256,1) for a predictors and a tensor of (1,4,1) of labels

Image | Predictor | Classes



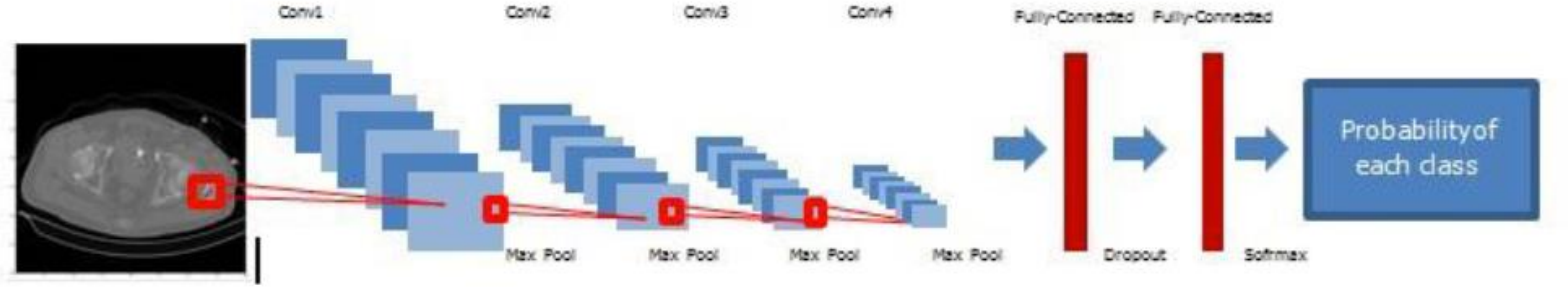
$$v_1 = (a_{11}, a_{12}, a_{13}, \dots, a_{1n})$$
$$v_2 = (a_{21}, a_{22}, a_{23}, \dots, a_{2n})$$
$$v_3 = (a_{31}, a_{32}, a_{33}, \dots, a_{3n})$$
$$v_m = (a_{m1}, a_{m2}, a_{m3}, \dots, a_{mn})$$

array [1,0,0,0]
array [0,1,0,0]
array [0,0,1,0]
array [0,0,0,1]

Image transformation was needed to fit in computation power and increase accuracy

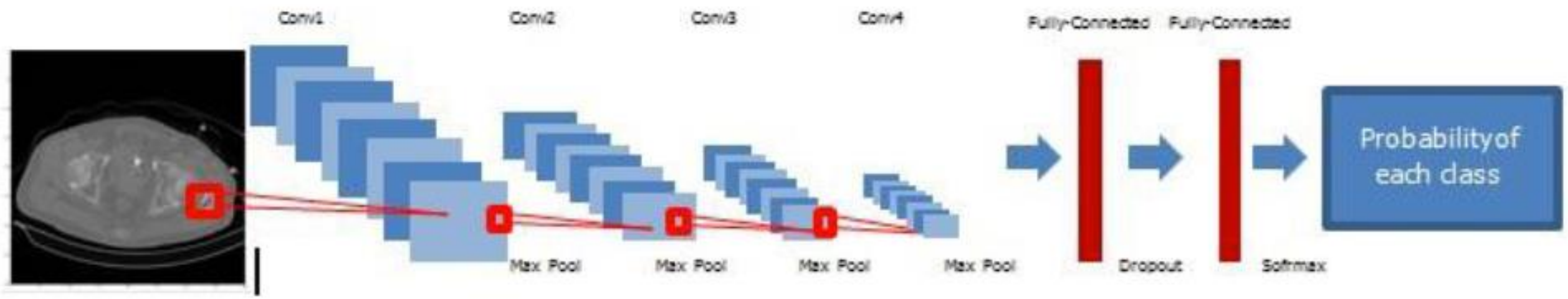
Neural Network Architecture

- Used a 6 layer convolution neural network
- 4 layers of 2d convolution strides =[1,1,1,1] and padding=‘sample’
- 2 layers of Full Connected with dropout
- Softmax layer for multinomial classification
- Max Pool with 2x2
- Relu as activation function



Results

- Classification outcomes are related to 4 classes: T2a, T2b, T3a and T4a
- Using the ConNet, Top 1 accuracy increases achieving 81.30%
- Baseline using a Multinomial Logistic Regression we achieved Top 1 accuracy 72.27%



Lessons Learned

- GPU and CPU memory are more relevant in your hardware than cycles
  - OOM errors are very common when we use medical data; unless your model take weeks to run, it is better to have more memory to fit all your weights initialization and mini batch process
  - If your model takes weeks to run, it is better to improve memory and cycles or use a distributed platform

- Code Design
  - Image processing was a very time demanding phase: after applying several different types of image filters, we needed to train the CNN and test the model to see the Top 1 accuracy of the model which took time
  - Convolution Neural Network: we tried different CNN approaches, including 2,3,4 and 5 layers. How large is your CNN, it seems that it gives you better results, similar to ResNet.

Conclusion

- Convolution Neural Network Architecture has a positive path in Medical Images Diagnosis - an increase of accuracy from 72.3% to 81.3% shows potential to explore

- Some techniques to generalized CNN in Data Science:
  - Availability of more data in early stages cancer and record of clinical checkpoint with patients
  - Application of R-Fast-CNN with other CNN architecture (like ResNet) for image segmentation and classification

- Some techniques to generalize in medical domain:
  - Cover more types of primary tumors
  - Train independently CNN models for all planes (coronal, transverse and sagittal) using a voting criteria

Global Enablement For Cancer Study using Big Data and Deep Learning

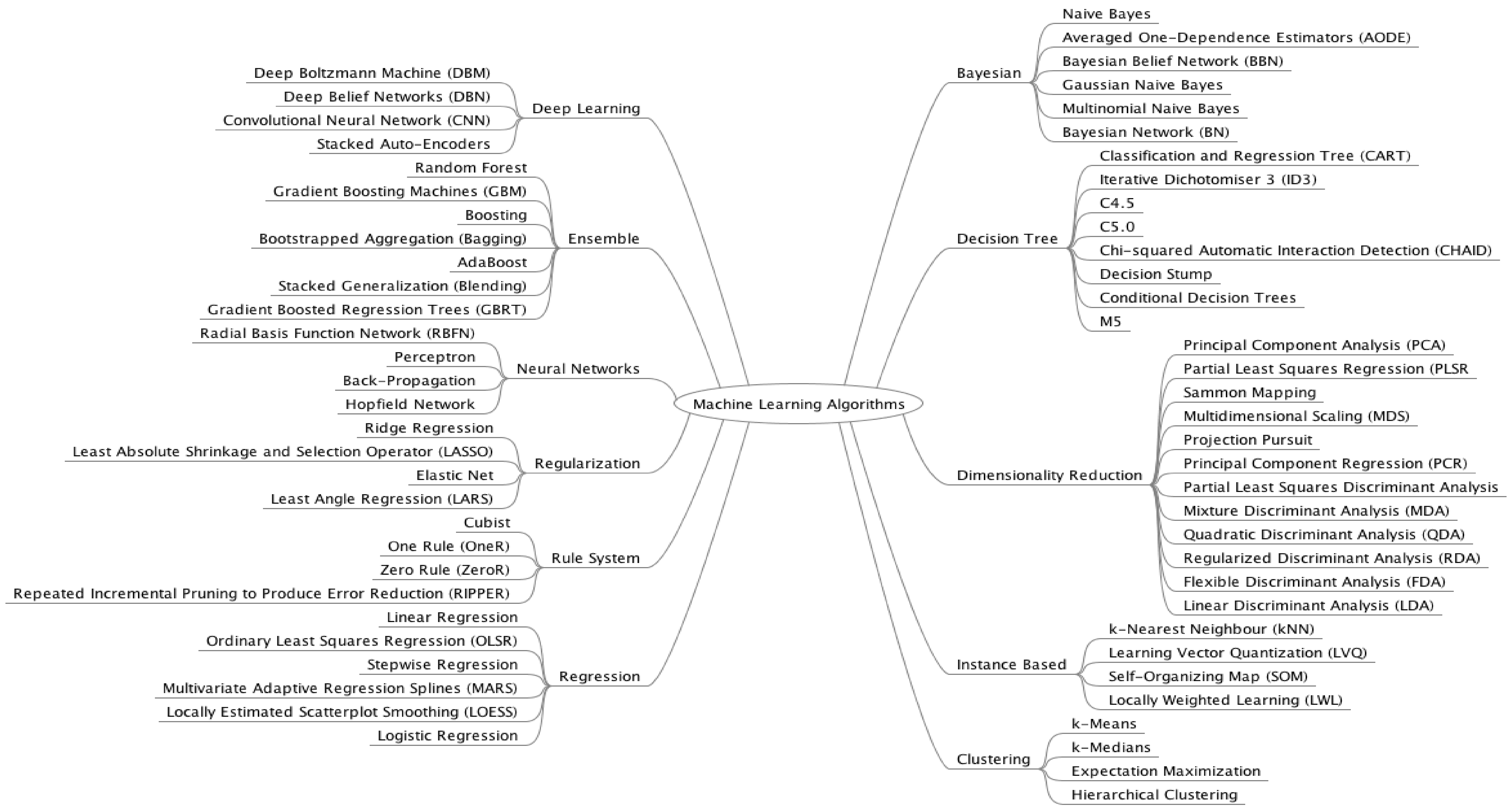
Samples of ML/DL Algorithms and Stack Selection

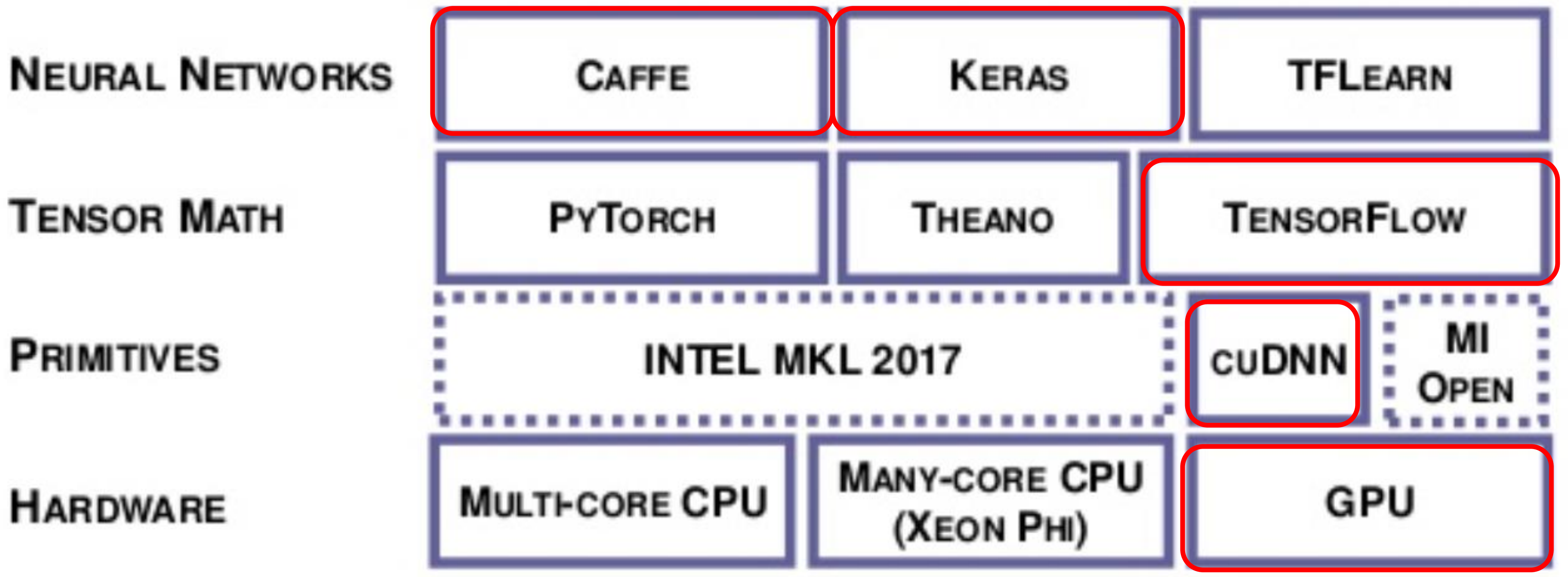
Criteria

- Identify inputs characteristics (continuous variables, categorical variables, text, log, image, video, voice)
- Verify Target variable (continuous vs. categorical and available vs. not available)
- Decide approach (supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning

Rules of Thumbs:

- Machine Learning Stack, Libraries
- Operating Big Data Ecosystem and Development
- Speed, Visualizations, Production





Dell EMC Medical Analytics Factory Model 2.0

FACTORY LEAD | **BUSINESS/TECH ANALYSTS** | **ANALYTICS PIPELINE** | **TESTERS** | **DEPLOYMENT LEAD**

Prioritize

- Business owner communication
- Prioritize tasks
- Workforce and environment planning and provision
- Capacity provision
- Track backlog
- Progress communication

Classify

- Assess Complexity
- Functional evaluation to existing modules.
- Consolidate Determination
- Design review
- Common utility
- Consolidated use cases
- Workforce provision and review

Analyze: D E P P

Perform
- Descriptive Analytics (D): qualify use case data, extract data quality, density, distributions, skewness, and variable correlations
- Exploration Analytics (E): Explore hypotheses related to use case. Generate relationships among hypotheses, verify hypotheses and generate measurements.
- Predictive Analytics (P): perform root cause analysis, events linkages, outliers detection, forecast measurements by ML or DL.
- Prescriptive analytics (P): Convert Analytics output into business actionable, Plan A/B Tests, and tracking outcomes.

Test

Conduct
- Analytic model code test,
- API wrapper code test
- Performance test
- Unit Test,
- User Test,
- Business APP Integration test
- *Execute A/B Business Test

Deploy

Coordinate and Manage
- Rollout planning
- Training
- Documents
- Deployment planning, business app

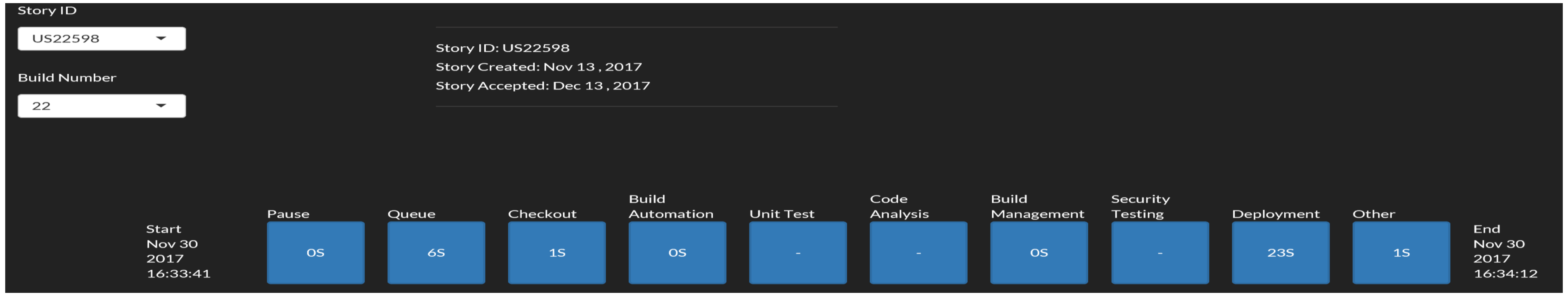
PROCESSES MINING

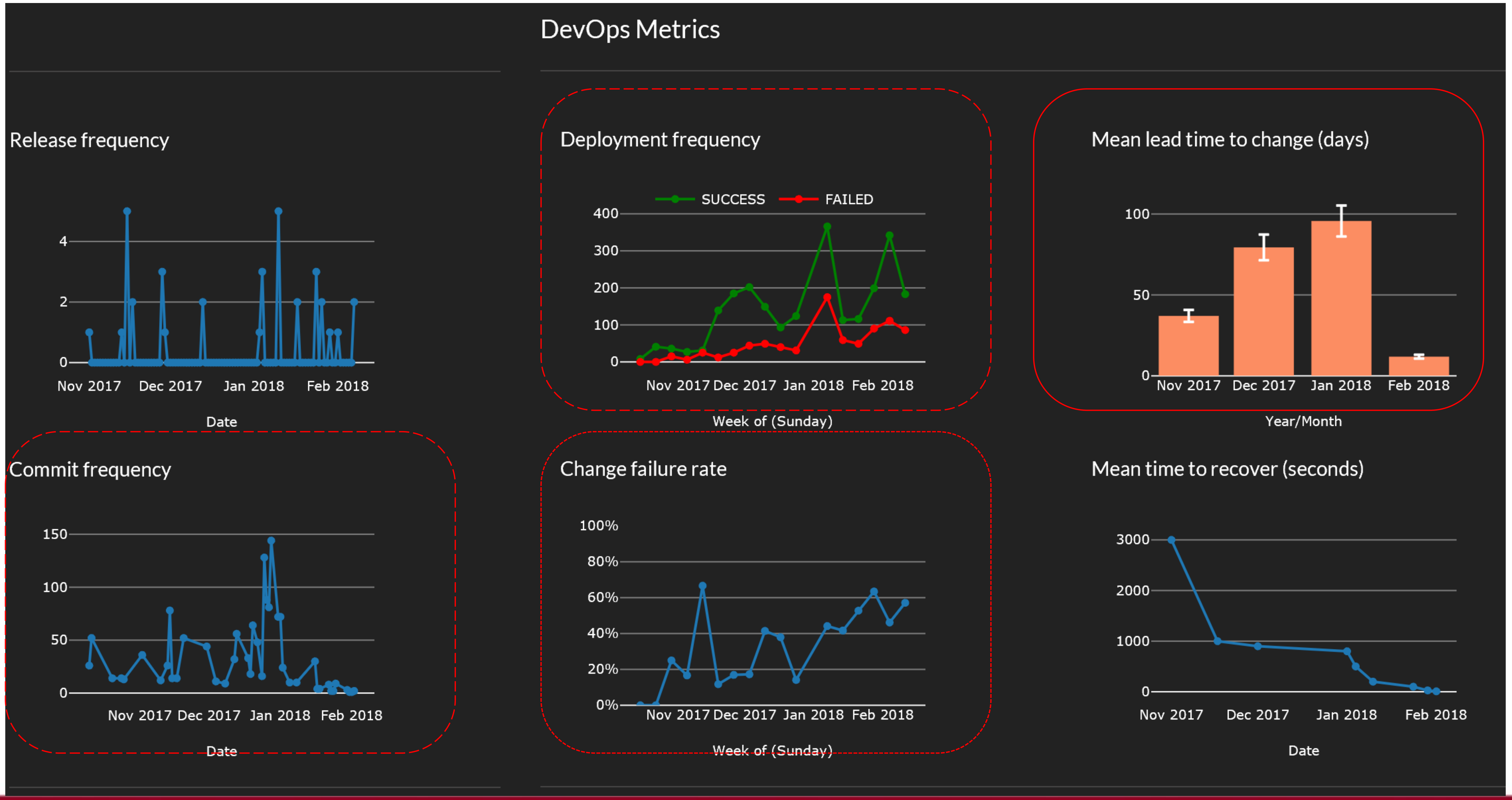
Statistics of DevOps KPIs: Counts/ time based distributions of Pause, Queue, Checkout, Build Automation, Unit Test, Code analysi, Build management, Security Test, Deployment, release frequency, commit frequency, Deployment frequency, Change failure rate, mean lead time to change, mean time to recover, …

- Reasons, Priority, Backlog, funding .. Analytics Factory KPIs/Metrics (AKM)
- Duration, impacts, expected performance, common design patterns, .. AKM
- Data sources quality, sys owner, ready capacity, accept/reject AKM
- Hypothesis trending, data enriching AKM
- Accept/reject, ROC tracking, re-train performance ,.. AKM
- Business process integration counts .. AKM
- Test tracking, tickets trending, performance distributions, .. AKM
- Deployment, user experience, Expected vs. Real ROI tracking, .. AKM

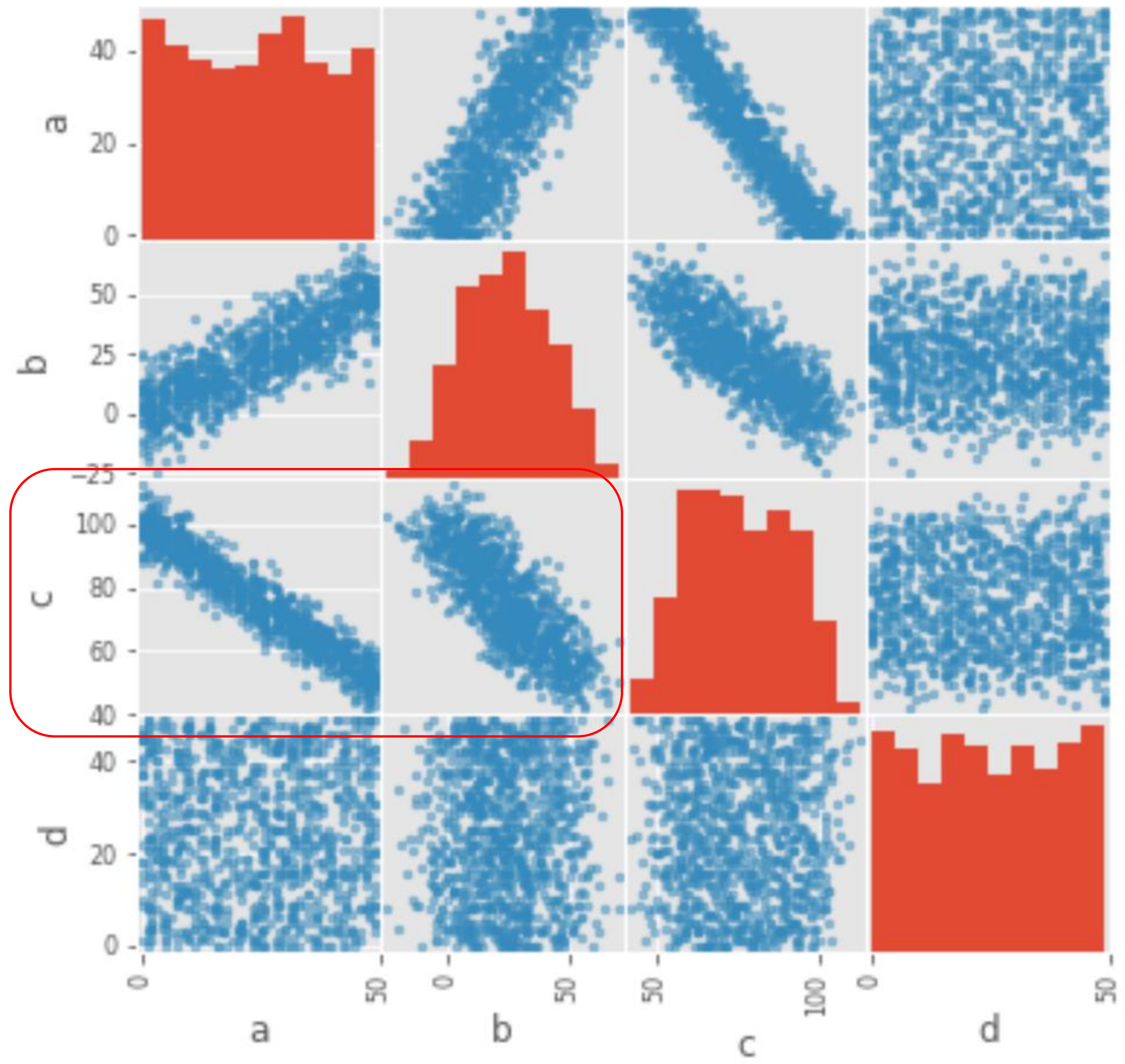
Processes Analytics: Root Cause, Caucasity Analysis, Data Center predictive maintenance (Hardware, software, APPs), Customer ROI trend, .. Complex event process improvement, ..

Process Mining Example






```
pd.scatter_matrix(df, figsize=(6, 6))
plt.show()
```



Increase trend of change failure rate induces

- Low production commit frequency
- Low deployment frequency
- Low mean lead time to changes

Process Mining Initial and Ongoing Steps Example

Step 1: Establish hypothesis

Hypothesis
*CMs have "quality production ranges" where production outside of those ranges have **Lower** than acceptable quality problems*

Step 2: Identify and quantify predictive variables

Variables	F(x)	Var σ
CM Recent Performance Score	.67	2.50
Supplier x Component Quality Score	.62	3.25
Product Complexity Score	.59	1.25
Test Suite Score	.58	3.60
Seasonality	.51	1.14
Platform Stability Index	.49	4.55
Extreme Weather		
…..		

Step 3: Build CM Profiles

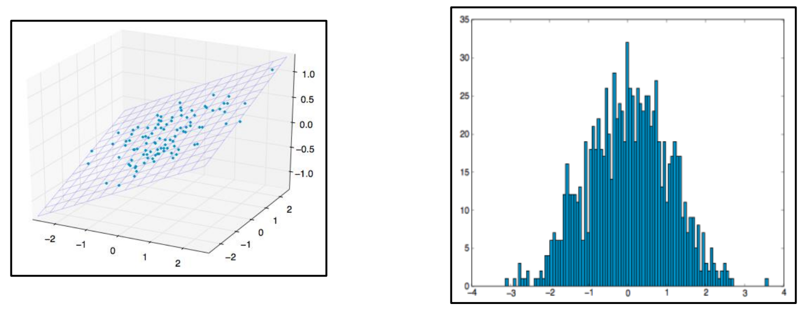
JAB Profile

GB Profile

FOC Profile

$$y_i = \sum_{j=1}^{D} w_j x_{i,j} + \epsilon_i = \mathbf{w} \cdot \mathbf{x_i} + \epsilon_i$$

$$\arg\min_{\mathbf{w}} J(\mathbf{w}) = \arg\min_{\mathbf{w}} \sum_{i=1}^{M} (\mathbf{w} \cdot \mathbf{x_i} - y_i)^2$$



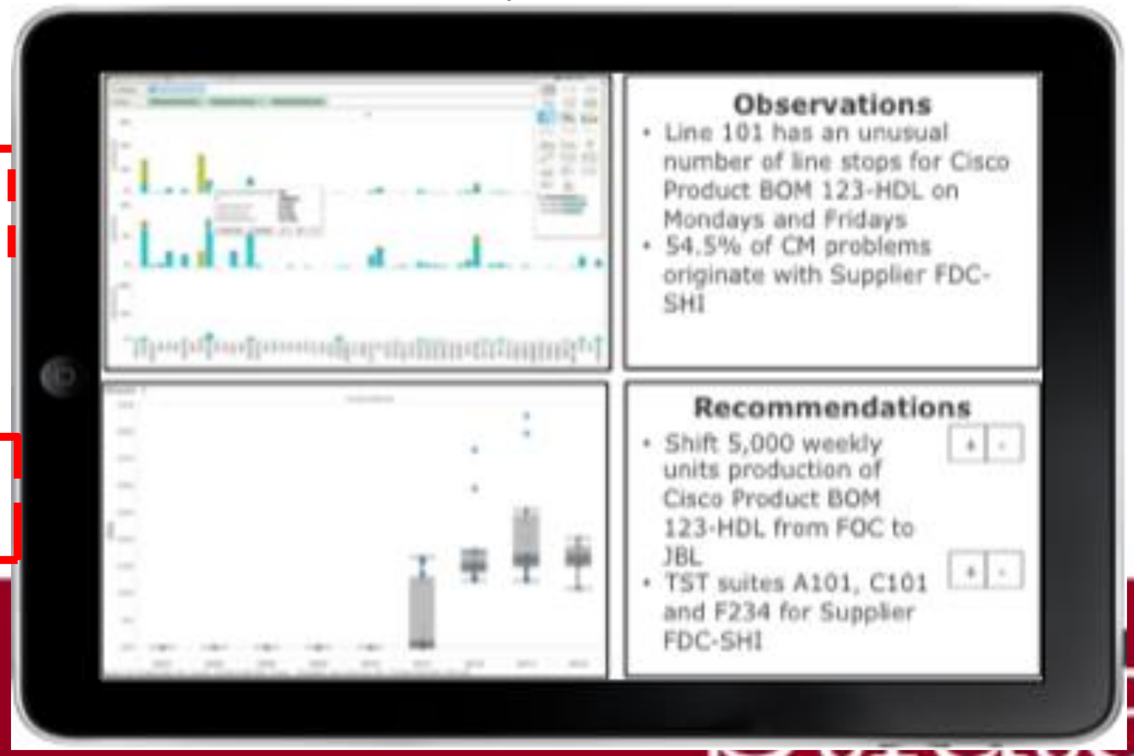
Step 4: Monitor data feeds against profiles to flag anomalies

- BU develop x Software modules Component DPPM
- Suppler x Component TST
- PCN
-
- Day of week
- Local weather
- CM Newsfeeds
- Local economy

Step 5: Refine Profile variables

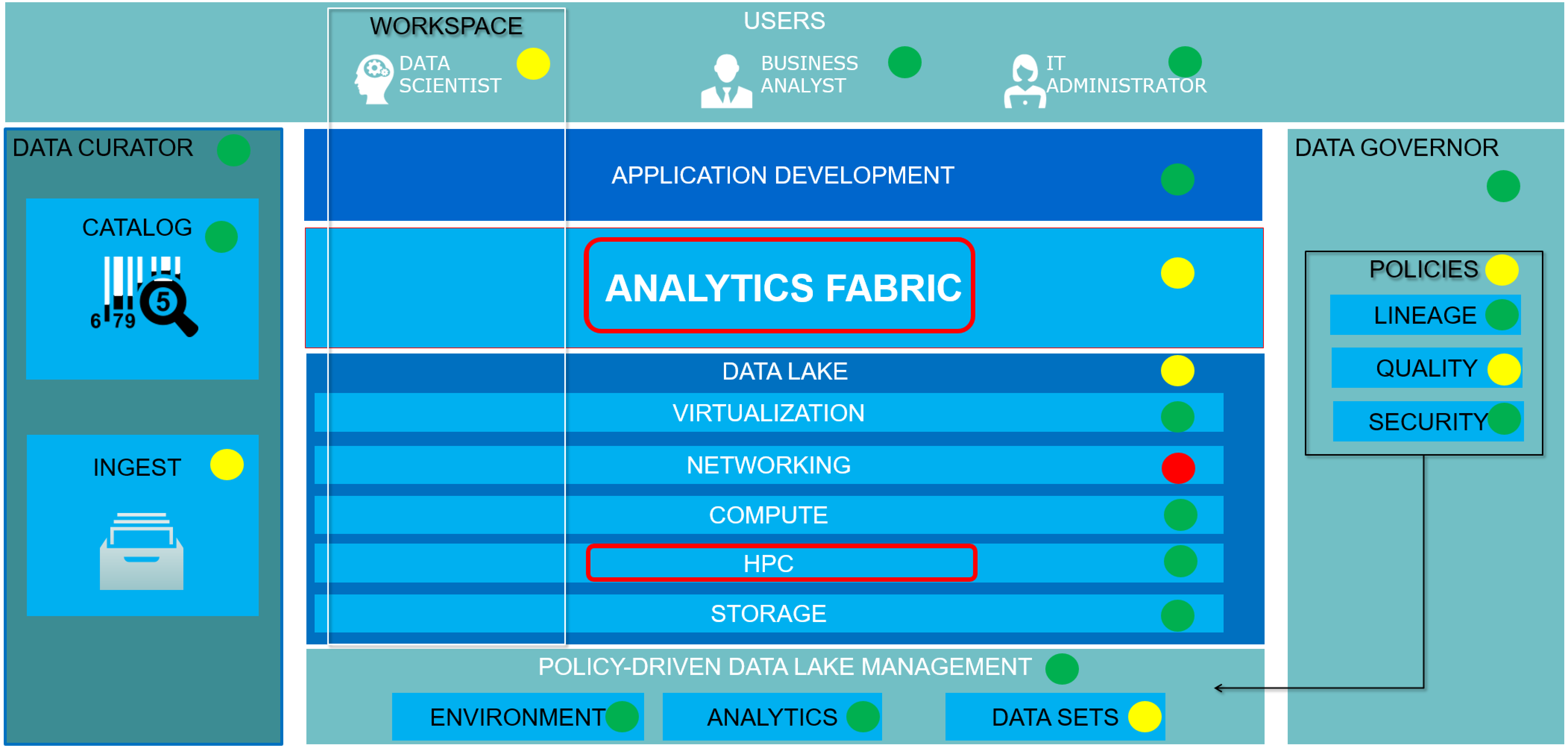
- Reduce variance
- Add new variables
- Delete variables

Step 6: Publish CM Quality and Rework Scores & Recommendations



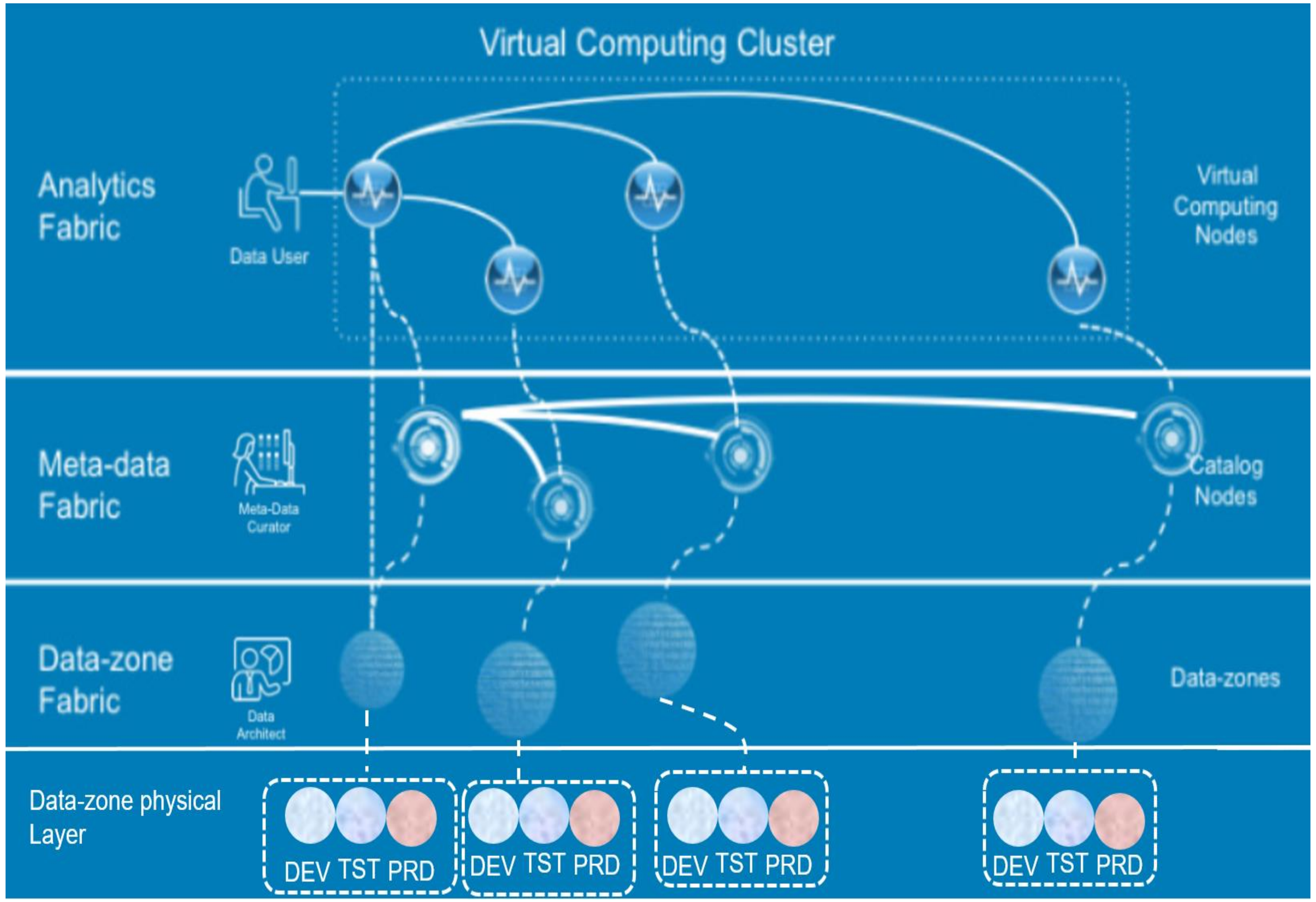
Analytics Factory Efficiency Logical N-Tiers View

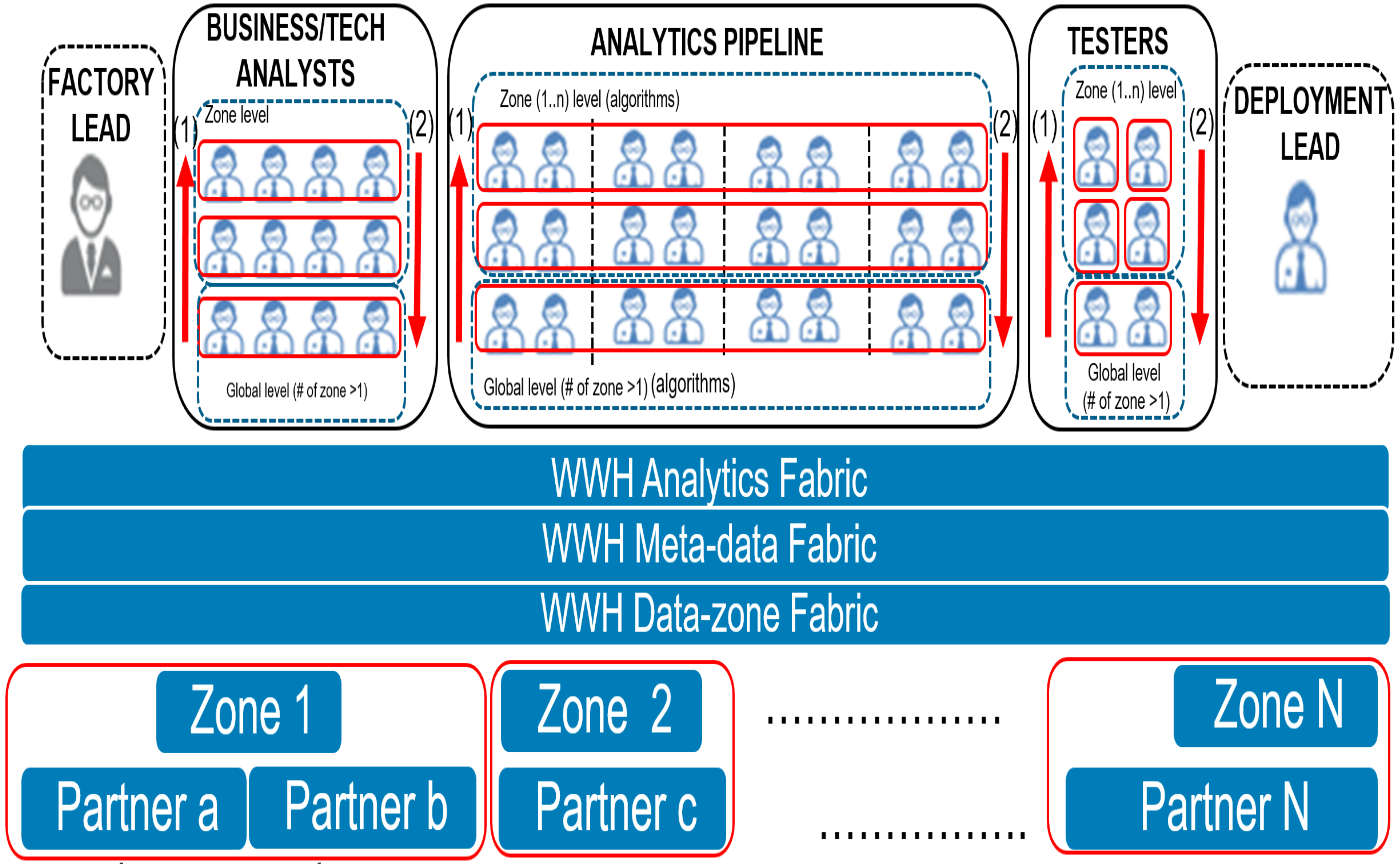
LOGICAL VIEW



Dell EMC Medical Analytics Factory with Dell EMC WWH* for Global Deployment and GDPR Compliance

- Share "Knowledge" without disclosing PII and PHI
- Operating Big Data ecosystem and development facilitated by processing management
- Distributed algorithm design and testing (step 1, 2) and analytics model training and sharing deployment





*WWH: https://blog.dellemc.com/en-us/world-wide-herd-disease-discovery-and-treatment/

Q&A

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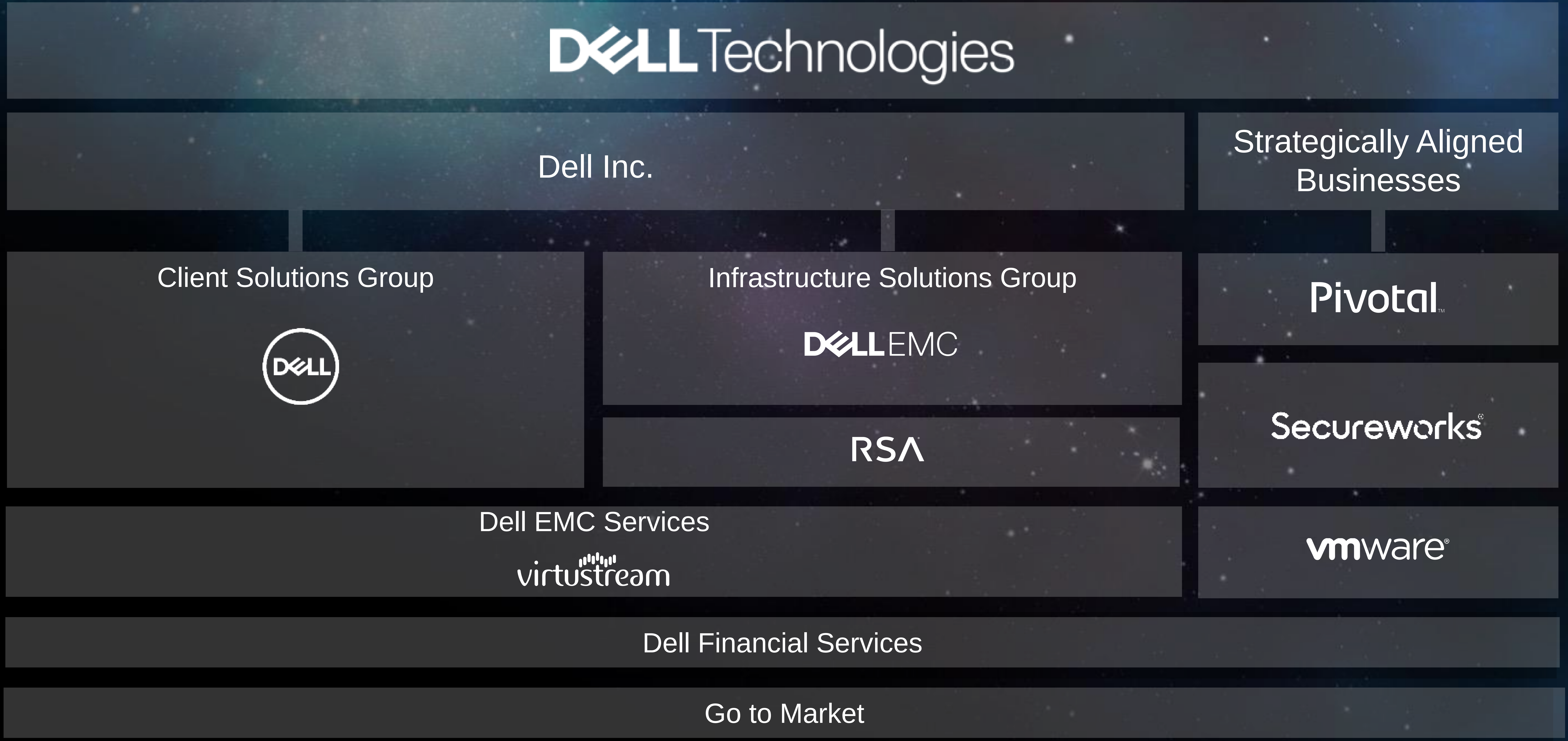

This slide represents Dell Technologies' operating structure. Our financial reporting structure consists of three business units: CSG, ISG, and VMware. Our other businesses include the results of RSA, Pivotal, Secureworks, and Boomi.