mechanica ai

ML-based services for manufacturing: from reproducibility to automation

Emeli Dral
Chief Data Scientist

Speaker

Now

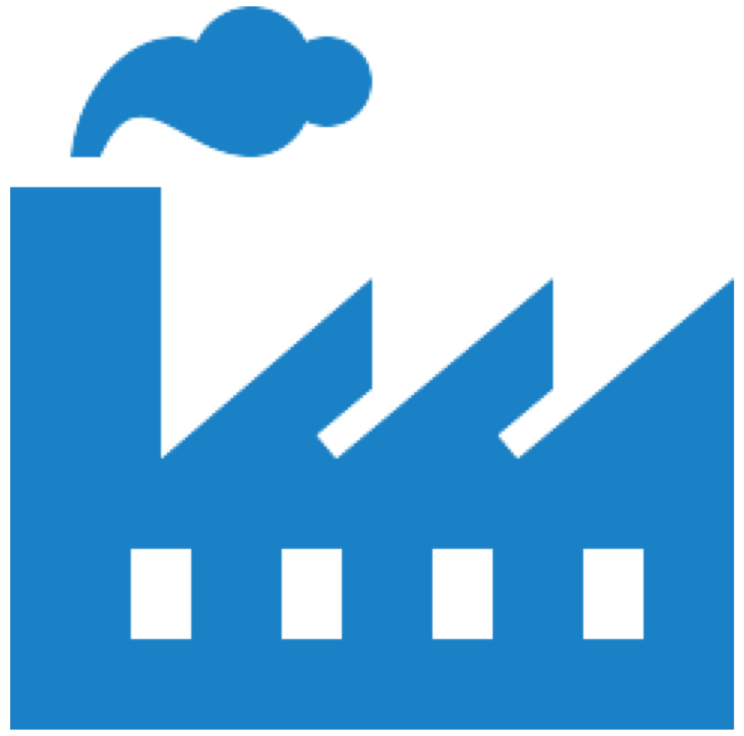
- Chief Data Scientist в Mechanica AI
- Teaching at Coursera, Harbour Space, SHAD

Earlier

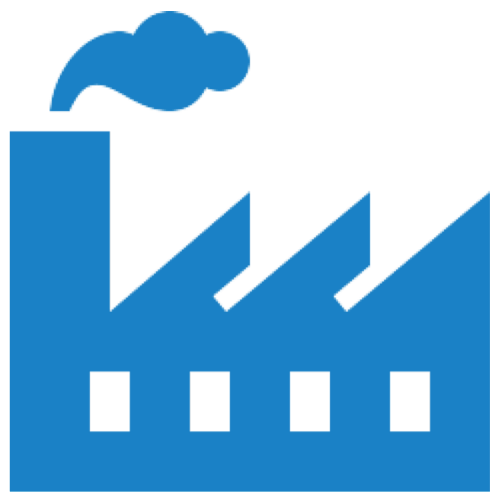
- Chief Data Scientist Yandex Data Factory
- Data Scientist at Yandex
- SDE at Rambler

What is manufacturing ML?

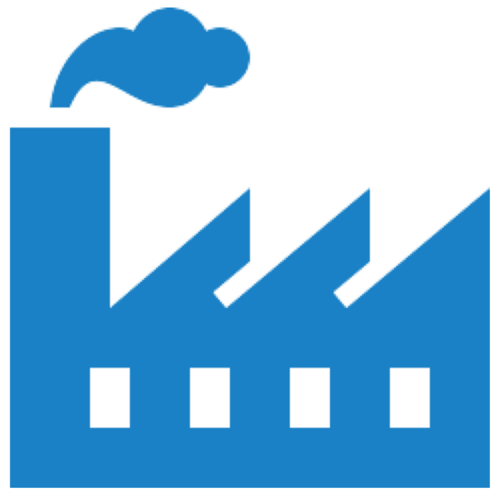
Math is always the same



Expectations are differ

		
Expectations	• «Improved the process by 5%? Too good to be true..»	• «It would be nice to increase the conversion two times. Will AI help with that? "
Culture	• Know what regression is without us • There is a culture of data collection and experimentation.	• Learn to be data-driven • Sometimes they can afford to test hypotheses in production ☺

Same with requirements

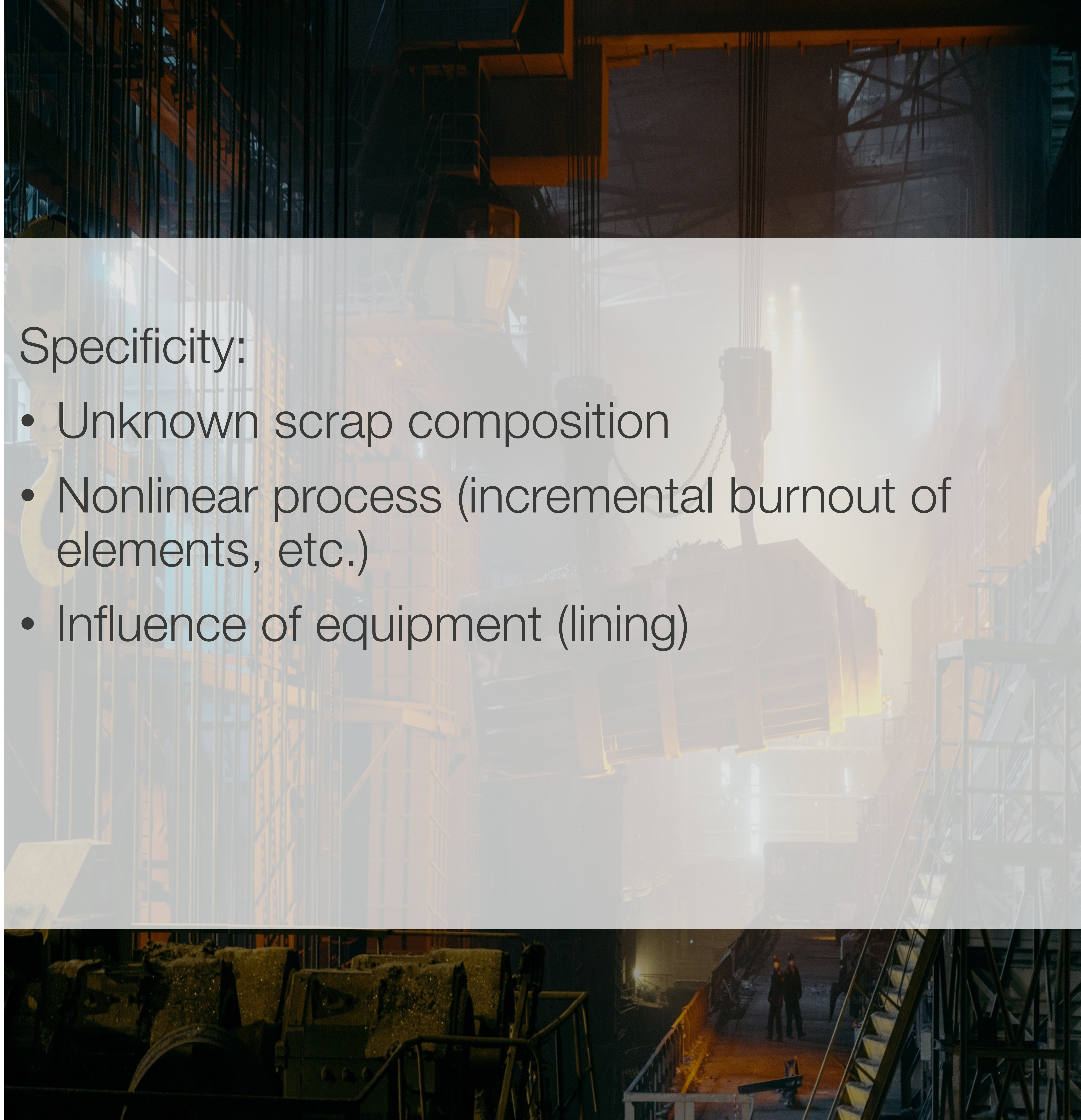


Requirements	• “Physical” model behavior • Safety and reliability	• Optimization is everything
Cost of a mistake	• We got 10 tons of defects • Expensive unit is broken • The operator does not know what to do in a difficult case	• A customer received a bad advertisement. • No recommendation block was displayed. • Bot said nothing or said stupidity

Metals

Optimization of raw materials usage in steel production

- Costly Additives - Ferroalloys
- Task: to reduce the total consumption when stay into the target chemistry



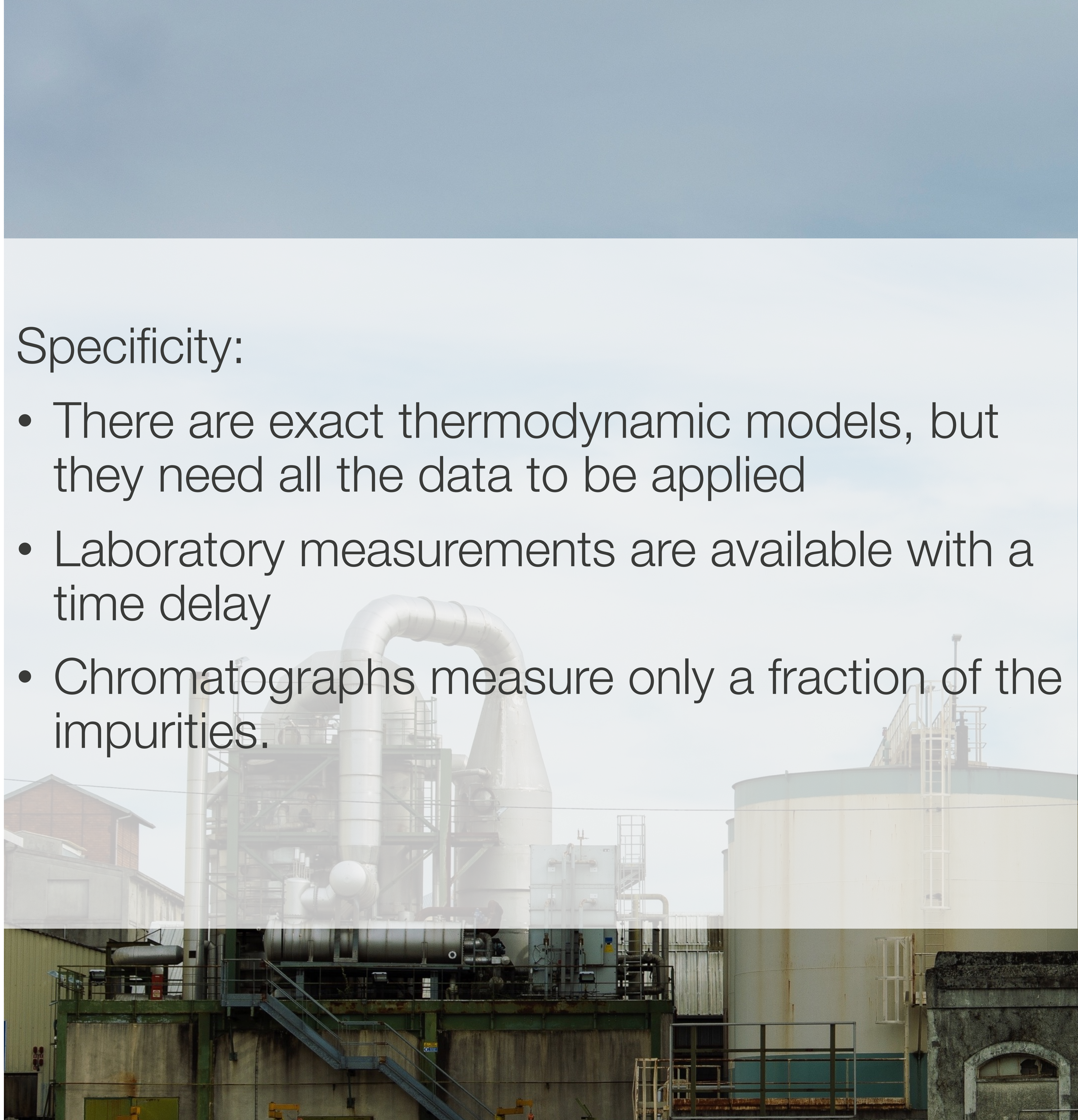
Specificity:

- Unknown scrap composition
- Nonlinear process (incremental burnout of elements, etc.)
- Influence of equipment (lining)

Petrochemistry

Virtual measurement of the composition of the input gas during fractionation

- The composition of the input gas changes
- The composition is important for optimal process control.
- Task: to evaluate the composition in real time



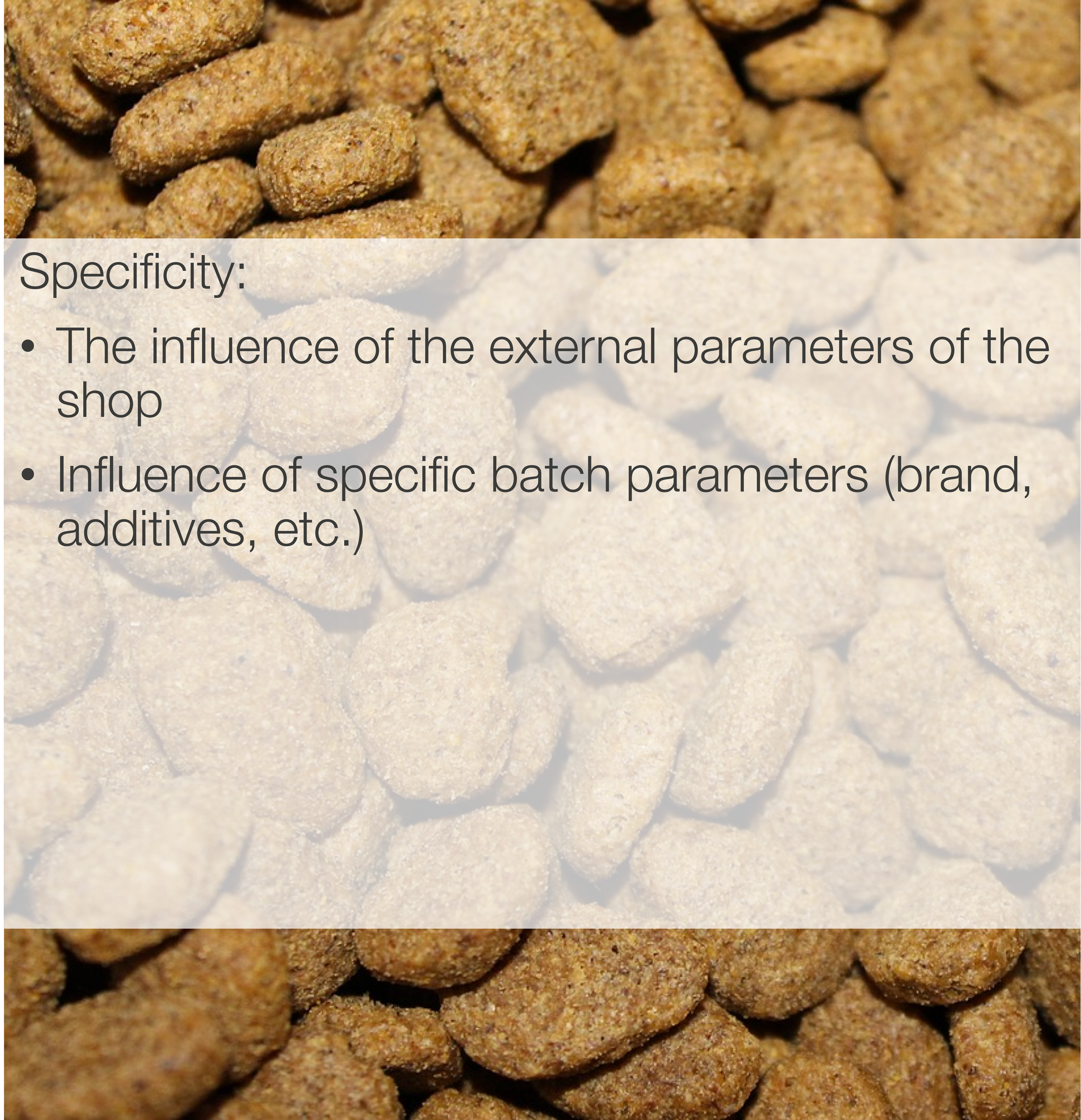
Specificity:

- There are exact thermodynamic models, but they need all the data to be applied
- Laboratory measurements are available with a time delay
- Chromatographs measure only a fraction of the impurities.

Food industry

Product moisture prediction

- The product passes through the dryer.
- Each batch is slightly different.
- Objective: to ensure the optimum moisture content of the product at the final stage of production.



Specificity:

- The influence of the external parameters of the shop
- Influence of specific batch parameters (brand, additives, etc.)

Reproducible research

Data specificity

Sources:

- process control systems (ACS TP, MES, APC)
- sensors
- equipment

"Manual" data:

- Quality Passports
- Production journals

Difficulties

Difficult to extract:

- MES- and other systems are not suitable for data analysis.
- Large volumes of poorly structured data

Difficult to handle:

- High noise when collecting data
- High pass level
- The accumulation of measurement errors and systematic errors

Who currently work with this problems?

- Manufactory itself
- System integrators/Consulters
- Software/Technology corporations (large ones)
- AI/ML startups
- OEMs

Who currently work with this problems?

Companies have following specialists on cite:

- Technologists
- Process engineers
- Analysts
- Junior and middle DS
- Junior and middle SDE

Skills and problems

Top-ranked skills:

- domain expertise
- classical models, mostly based on the specific tools (e.g. aspen ++)
- visual programming/analytics tools
- SQL
- analytical-grade code, mostly in interpreted programming language

Skills and problems

Top-ranked skills:

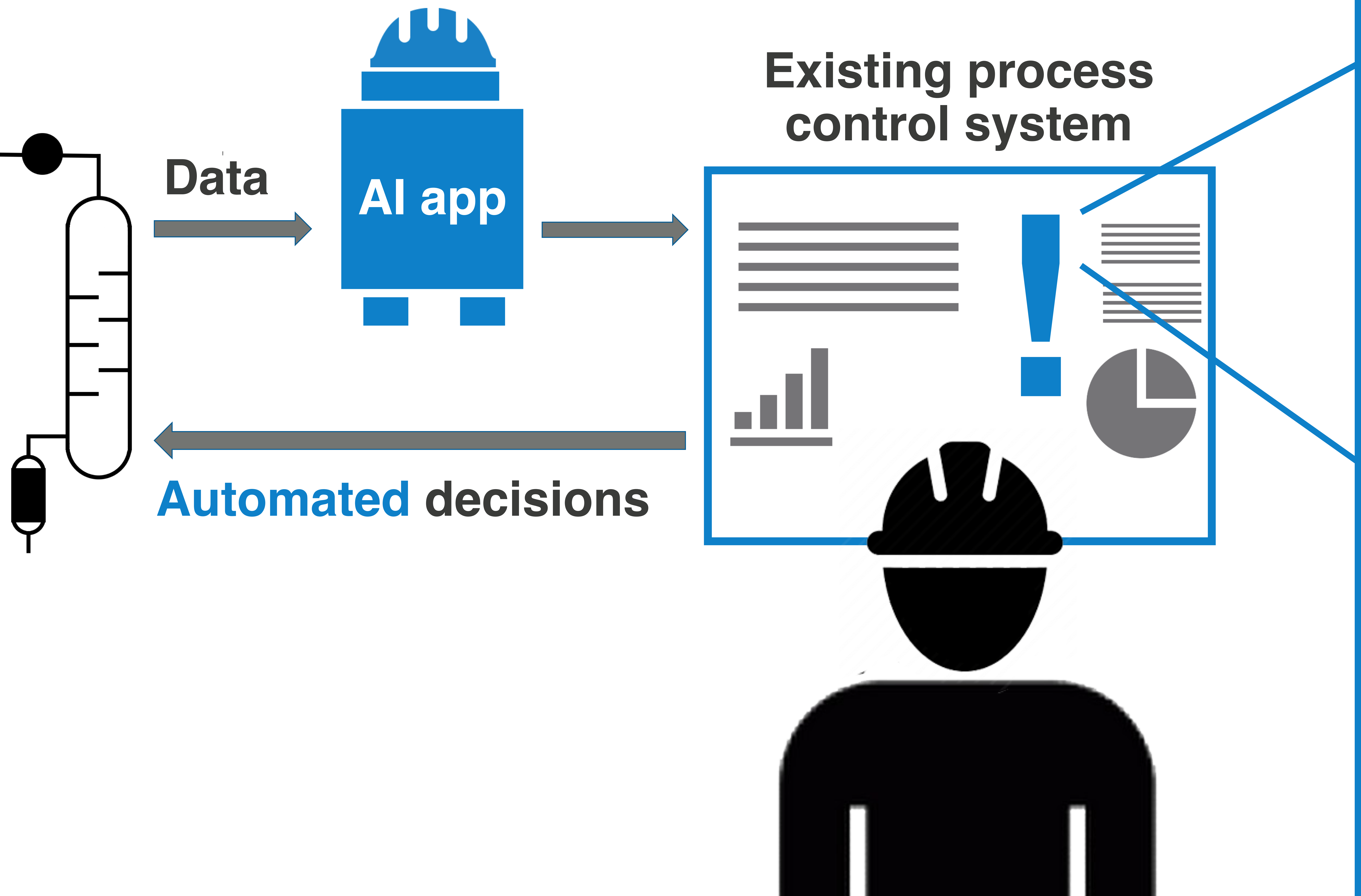
- domain expertise
- classical models, mostly based on the specific tools (e.g. aspen ++)
- visual programming/analytics tools
- SQL
- analytical-grade code, mostly in interpreted programming language

Top ranked difficulties:

- production-grade code
- developing services on top of ml models
- shipping services to production, integration issues (especially on the edge)
- support services, monitor and update them
- sensor data issues: downloading, cleansing, smoothing, NA filling, aggregation, alignment, joins/merges

Models vs services

Model -> software application



Measurement
(virtual sensor)

Prediction

Recommendation

Prescription
(automation)

Reproducible research

- Component solution architecture
- Libraries and reusable code
- Computational DAGs with versioning, dependencies and changes tracking

Production-grade services

- Service templates, simple deployment and integration
- Quick transition from analytical code to production one
- Quality monitoring, alerts
- Automatic models retraining
- Automatic quality assessment
- Automatic model update
- On edge deployment

What tools should be kept in mind?

1. Libraries
2. Templates
3. Workflow-managers
4. Docker-based build and integration
5. Component architecture

What tools should be kept in mind?

1. Workflow-manager:
    - reproducible experiments
    - DAG of computing nodes (not only ETL): sequences, dependencies and statuses
2. Docker-based build and integration
3. Component architecture
4. Libraries
5. Templates

What tools should be kept in mind?

1. Workflow-manager
2. Docker-based build and integration
   - automation of solution built
   - automation of testing procedure
   - automation of solution updates during production usage
3. Component architecture
4. Libraries
5. Templates

How platform is going to solve it?

1. Workflow-manager
2. Docker-based build and integration
3. Component architecture
   - ready-to-use blocks, implemented by professional developers (e.g. connectors to data warehouses, including industry-specific ones, such as SCADA or MES-systems)
   - reuse of blocks, implemented by team members earlier: no copy-paste, no reinvent the wheel, but lots of customization
   - standardize development inside team: ordering of standard blocks, especially technical ones (connectors, monitoring, etc.)
4. Libraries
5. Templates

What tools should be kept in mind?

1. Workflow-manager
2. Docker-based build and integration
3. Component architecture
4. Libraries
   - sensor data specific functions (mostly preprocessing, but not limited to)
   - autoML features in some sense
   - evaluation and estimation (incl. economic effects, model quality, statistics, a/b test results etc.)
5. Templates

What tools should be kept in mind?

1. Workflow-manager
2. Docker-based build and integration
3. Component architecture
4. Libraries
5. Templates
    - solution architectures set
    - ready-to-use baselines (DAGs) for standard cases and apps
    - easy scale of similar apps

Key components of success

- Use case scenario:
  - imagine we have a perfect model – how are we going to use it?
- Validated problem statement:
  - no need to train the model to learn that the prediction horizon is wrong
- Right data
  - is not about “big data”
- Right **tools and infrastructure for research & production usage**
  - environment that fits the task
- Combination of expertise
  - domain and data science

Questions?

Emeli Dral

emeli@mechanica.ai