Sensing is life

Steering LED chip production processes with AI

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ams OSRAM at a glance

5.04bn	**5,500+**	**20,000+**	**~24,000**
EUR revenues 2021	Engineers	Customers	Employees worldwide
~40/33/27%	**40+**	**15,000+**	**110+**
AUT/IM/Consumer revenue split FY 2021	Major R&D locations	Patents granted and applied for	Years design + manufacturing

IM – Industrial and Medical, AUT - Automotive

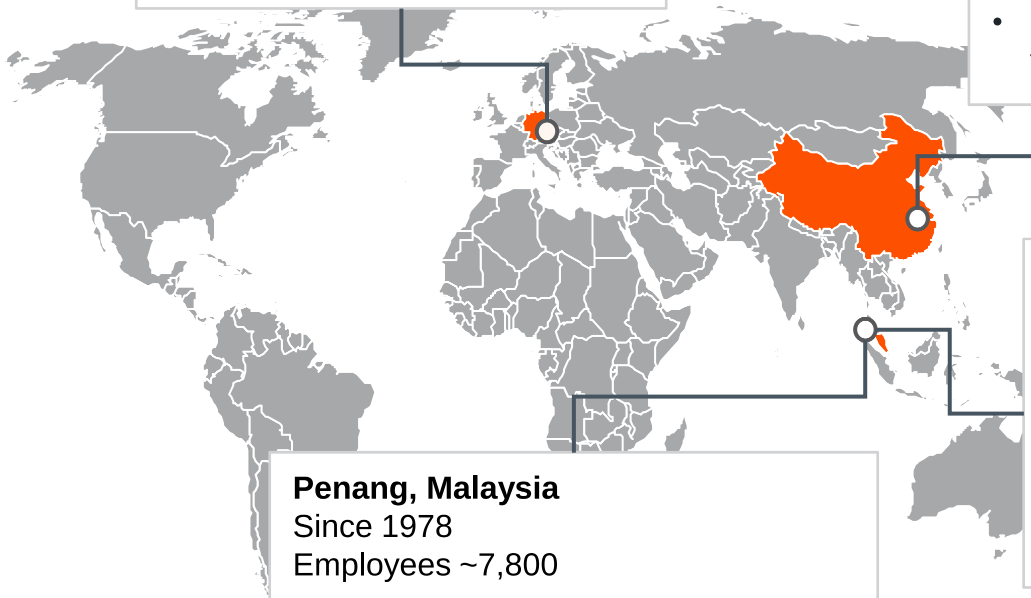
OSRAM Opto Semiconductors

Production sites and numbers*

1.7 bn € — **Segment revenue**

~12.700 — **Employees worldwide**

Global No. 2 — **Industry position**



Regensburg, Germany
Since 1972
Employees ~2,500

- **OS global headquarter**
- **R&D center** for chip and packaging technology
- **Chip production** for LEDs, IR and lasers
- **OLED production**

Wuxi, China
Since 2014
Employees ~2,200

- **R&D center** for LED assembly
- **Package assembly** for LED and IR

Kulim, Malaysia
Since 2017
Employees ~1,500

- **Chip production** for LEDs
- **Package assembly** for LED

Penang, Malaysia
Since 1978
Employees ~7,800

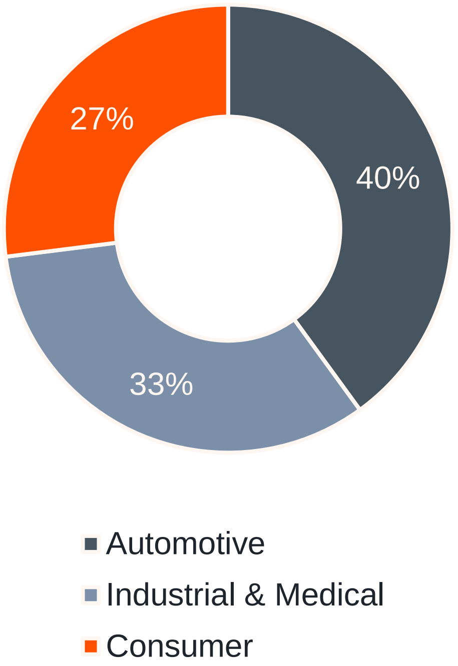
- **OS regional headquarter**
- **R&D center** for LED assembly
- **Chip production** for LEDs
- **Package assembly** for LED and IR

* from 2018

ams OSRAM: Leading in light emitters

OSRAM Opto Semiconductors – Key Products

Revenue by Market



Consumer

- Emitters for 3D sensing
- Sensing illumination
- Display
- IR Flash
- UV-C disinfection

Automotive

- Lighting (exterior/interior)
- 3D LiDAR
- Display functional lighting
- Ambient lighting
- Projection
- Intelligent forward lighting
- Adaptive driving beam

Industrial & Medical

- Sensing illumination
- Operation room lighting
- Sign and signal lighting
- Material processing
- UV-C disinfection
- Horticulture
- Outdoor/indoor lighting
- Stage lighting & projection

Kathrin Meindl

Short Introduction

- **2012:** B.Sc. Mathematics, University of Regensburg
- **2015:** M.Sc. Business Informatics, University of Regensburg
- **2015 – 2017:** Consultant, Big Data
- **2017 – 2020:** Big Data Architect, Cloud Development
- **2020 – now:** Data Scientist

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LED Value Chain

Front-end and Back-end production processes

Input | Output

Front-end

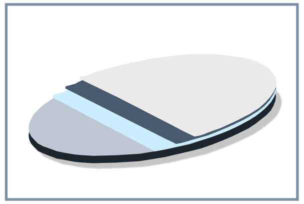
Substrates and others

- Substrates / wafer
  - Materials: Sapphire, GaAs, Silicon, ..
  - Diameters: 2 .. 6 inch
- Gases, metals, ..

Chip processing

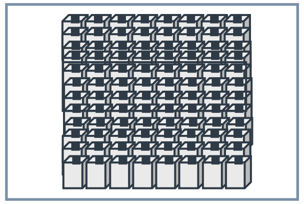
All process steps applied on wafer level, i.e., at the same time for later up to 100.000 chips !!

Epitaxy



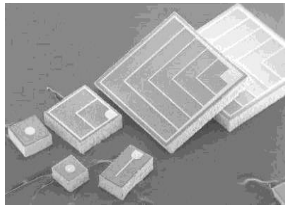
Coating & structuring

Singulation, testing



LED chips

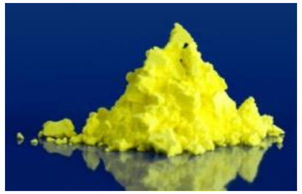
- Side length: 0.2 .. 2 mm
- Different light colors



Back-end

Chips and others

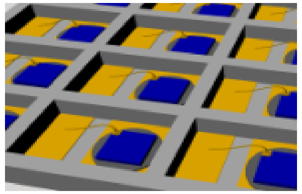
- Leadframes,
- Ceramics
- Silicones and glues
- Bond wires
- Phosphors
- ...



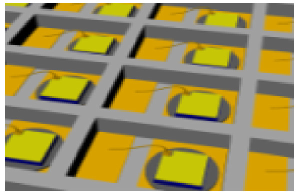
Processing

Process steps mostly applied to single devices or on small panels

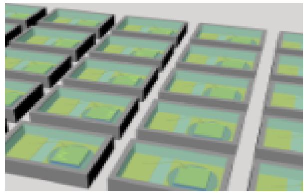
Die and wire bonding



Conversion

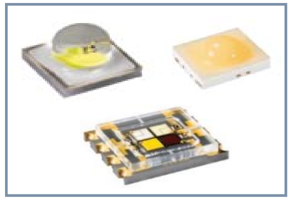


Sawing, testing



Packaged LED

- Power levels: 40mW .. 135W
- Packages mostly application specific



Frontend steering

Choosing the wafers that fit best to the customer demands for further chip processing

epitaxy

- epitaxy = crystal growth process on wafers
- mainly defines the LED output quality such as wavelength or brightness
- highly influenced by pressure, temperature, …

epi stock

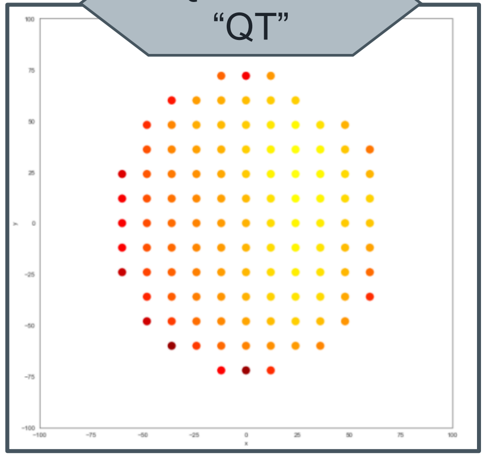
chip processing

- different chip processes can be applied to the same wafers and lead to different output qualities
- the best fitting wafers for the customer demands are chosen by a mathematical optimizer from the epi stock

Customer demand

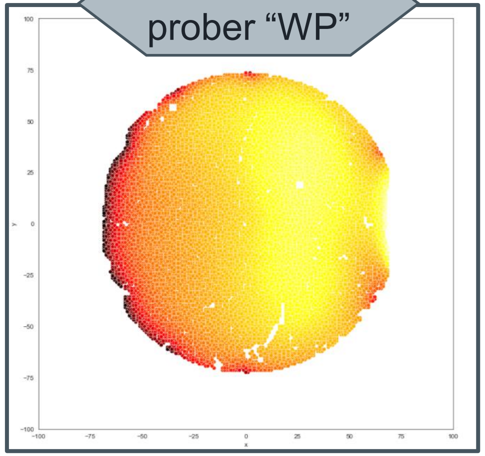
Input Quicktest:
sample measurements (<200 points) on the wafer after the epitaxy step

Quicktest "QT"



Output Waferprober:
each delivered LED chip is measured (up to 100k points per wafer)

Wafer-prober "WP"



Requires prediction of output LED chip qualities (WP) based on sample epi measurements (QT)

Challenges during exploration and ML design

The selected solution must fit for all products in a very diverse portfolio

Representative choice of test products

- high variety of products
- some materials or colors are harder to steer and hence have a higher variance
- different measurement types or sampling rates for products
- highly specialized low volume products

Preprocessing

- “big” amount of (semi-)structured data (variety of different measurement data and process transaction logs)
- some physical measurements have a low accuracy by design
- differing behavior on wafer boundaries

Machine Learning Experiment

Feature engineering

- limited to measurements that are integrated into the standard process for all products
- various influences on the production process and hence the output quality, e.g. production tools, materials, …

Choice / design of approach

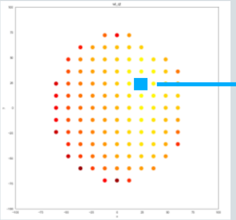
- accuracy has a direct business impact
- low runtime and complexity required
- should cover whole product portfolio
- feasibility of approach for new product qualities (extrapolation)

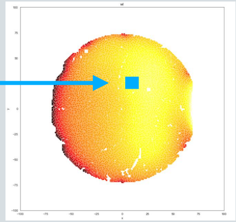
Different approaches for the prediction model

Setting measurements and their locations on the wafer into context

POINTWISE

Model maps single input value from quicktest to output value of the waferprober on the same location





PRO

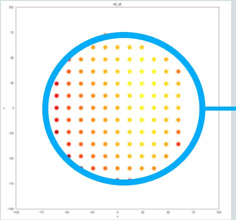
- can be used with most common regression algorithms
- works for small amount of data (< 200 points per wafer)

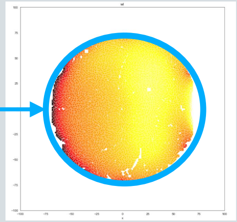
CON

- reduced accuracy due to limited data points in output

AREAS / WHOLE WAFER

Model maps single input value from quicktest to output value of the waferprober on the same location





PRO

- overall wafer structure and neighborhoods can be taken into account
- output can have more data than input

CON

- more complex algorithms / computationally expensive
- requires bigger amount of data

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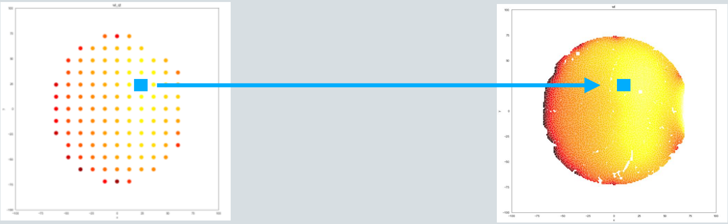
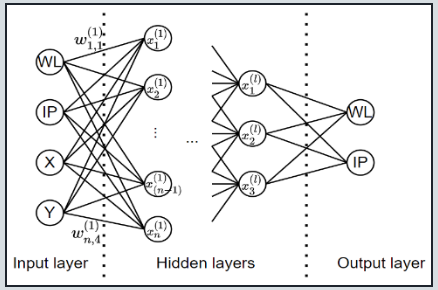
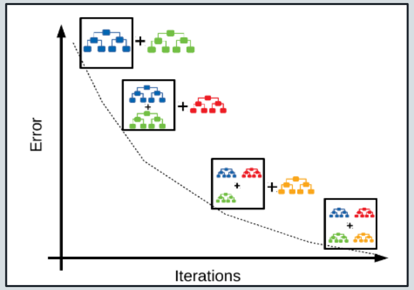


Neural Network



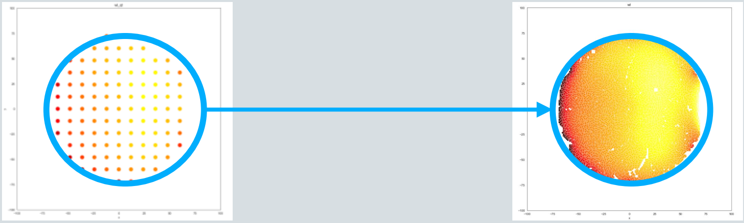
Gradient Boosting



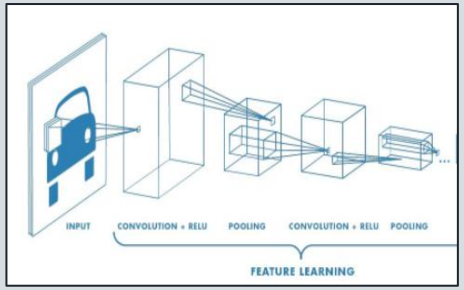
source: tvas.me

AREAS / WHOLE WAFER

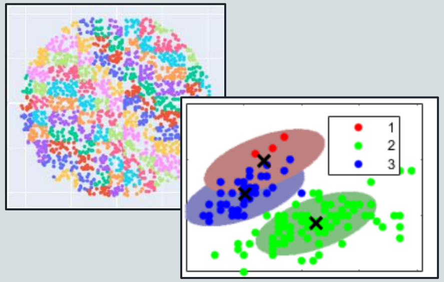
Model maps single input value from quicktest to output value of the waferprober on the same location



Convolutional NN (CNN)



Neighborhood Distributions



source: towardsdatascience.com

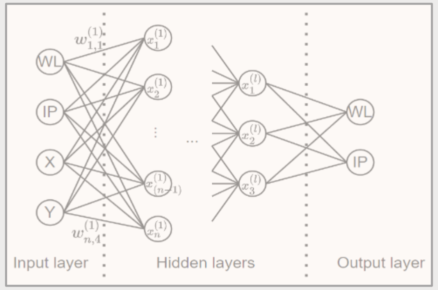
Different approaches for the prediction model

Setting measurements and their locations on the wafer into context

POINTWISE

Model maps single input value from quicktest to output value of the waferprober on the same location

Neural Network



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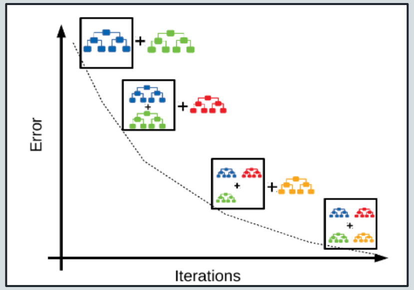


source: ivas.me

→ XGBoost selected as the best approach:

- good overall model performance for all test products
- low runtime and complexity of approach
- performs well with small amount of data, can handle low volume products

Handling of new product qualities

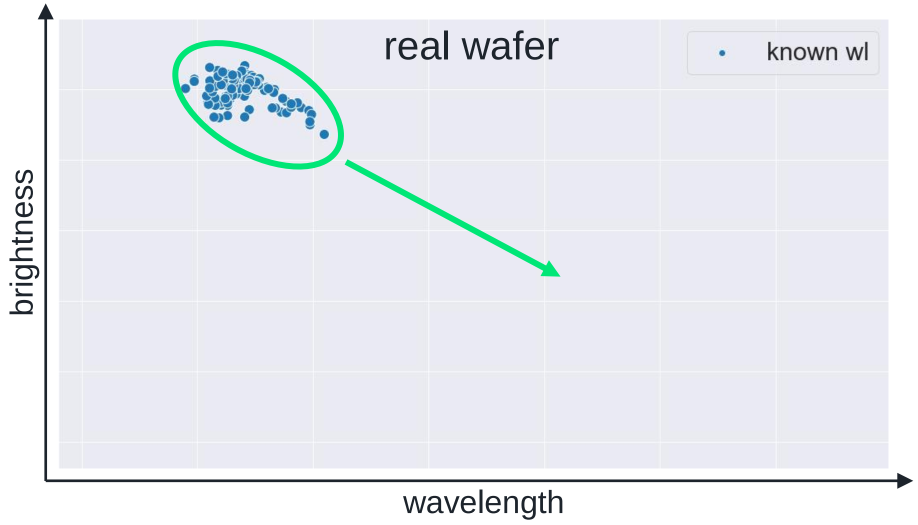
Generation of synthetic training data for new product qualities

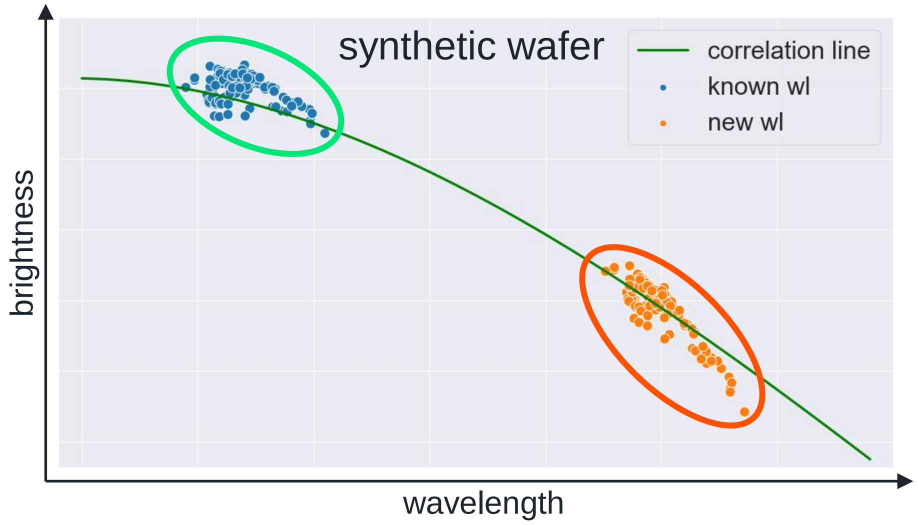
- **Problem:** The approach must be capable to also predict “new” product qualities. However, some ML algorithms can not handle extrapolation very well.

- **Solution:** Generation of synthetic data to train algorithm

- **Challenge:** Must generate **realistic** wafer measurements for all allowed wavelengths that don’t exist in the historical data:
  - Realistic density and distribution of measured qualities
  - Reproduce “patterns” on the wafer

- **Approach:** Shift / transform existing measurements
  1. Choose sufficient number of previously produced wafers
  2. Shift / transform all input (QT) and output (WP) measurements along the respective “correlation line” (based on existing measurements and physical dependencies between wavelength and brightness)





Thank you! Questions?