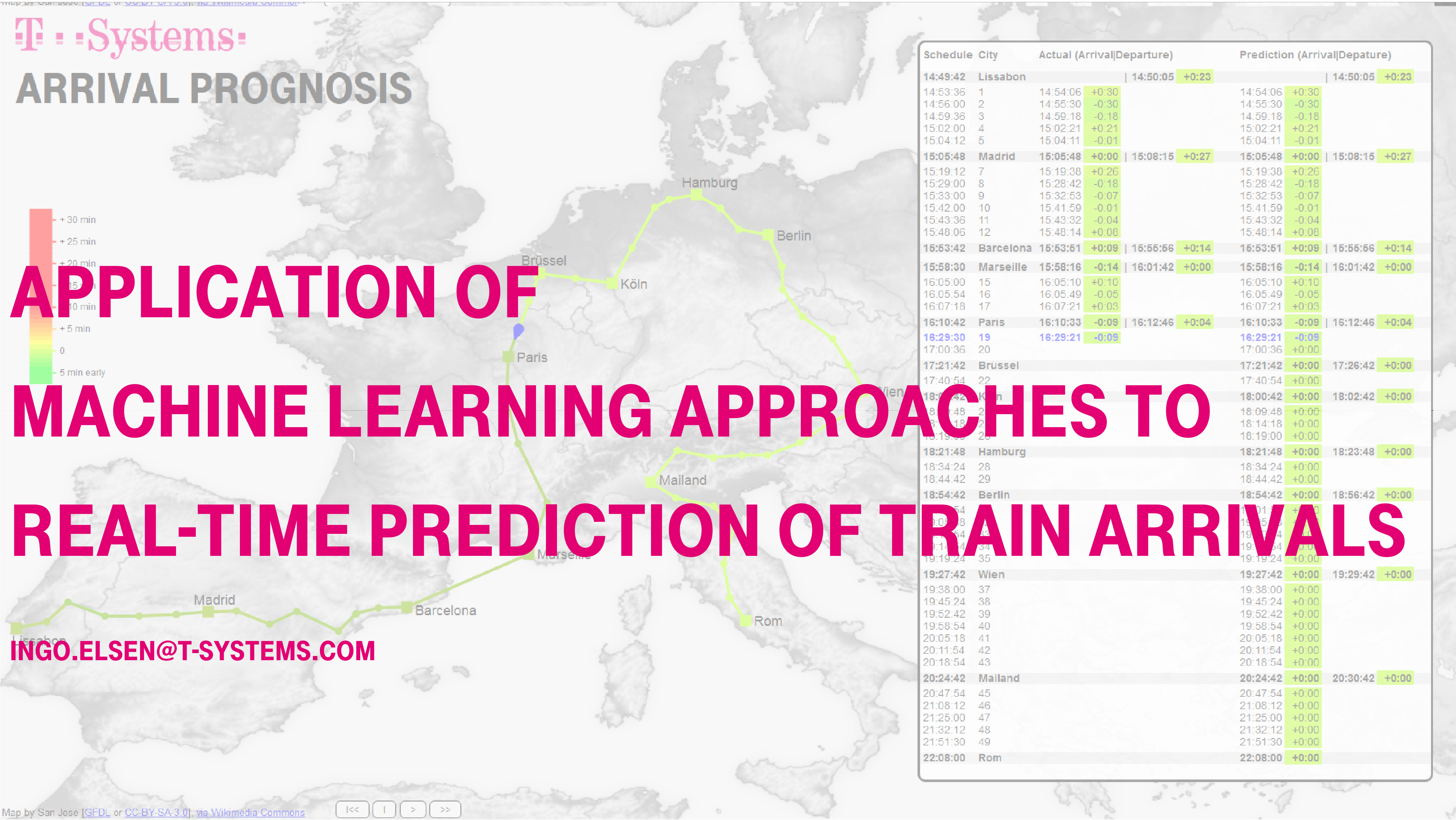
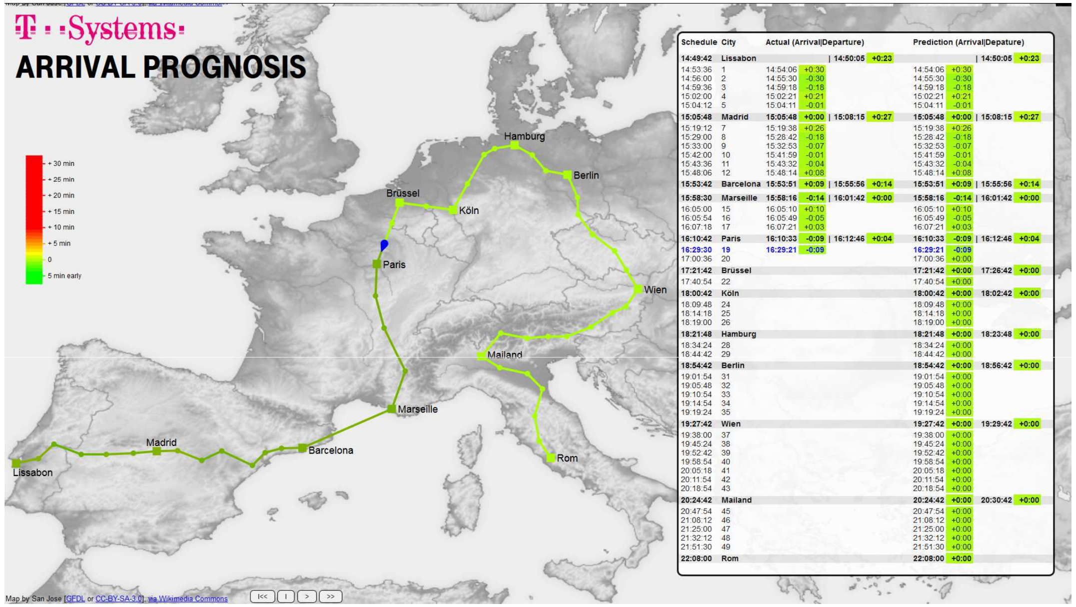


APPLICATION OF MACHINE LEARNING APPROACHES TO REAL-TIME PREDICTION OF TRAIN ARRIVALS

INGO.ELSEN@T-SYSTEMS.COM

TASK: PREDICT THE ARRIVAL OF TRAINS



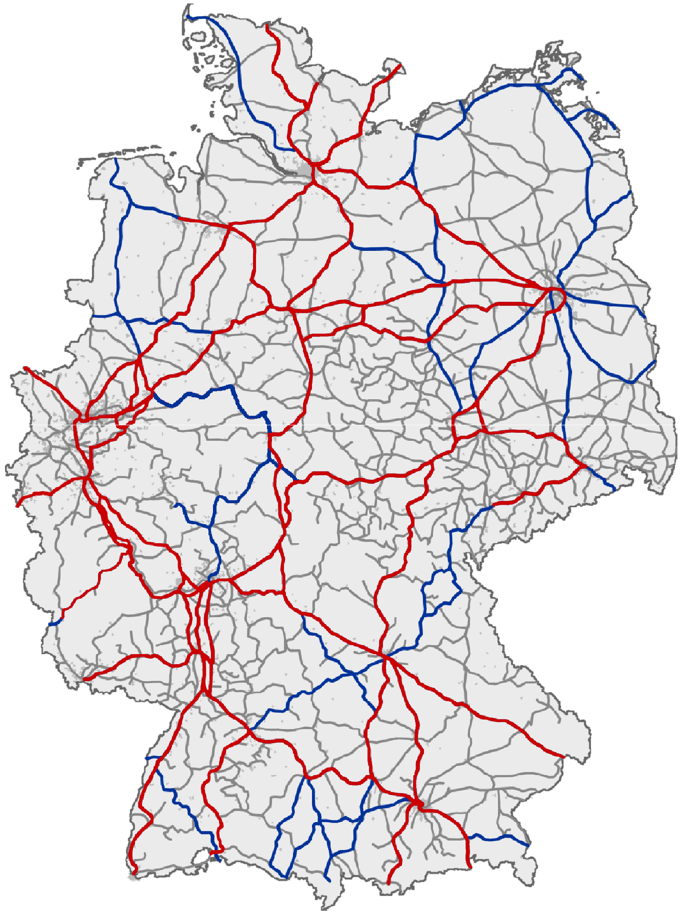
THE FIVE V'S: VOLUME, VELOCITY, VERACITY, VARIETY, VALUE

- 1bn datasets to process for learning
  → 22000 Neural Networks trained in 33 min
- Realtime requirement for operations (sub second latency)
  → <600us to predict a waypoint, two complete operational days predicted with <10min
- Data must be checked for validity
  → validation runs on each message received, prediction quality is continuously checked
- Multiple sources must be merged
  → trains, schedules, network ops systems, ...
- Improve passenger information for running and scheduled trains → > two times better than existing solution

MODEL: PREDICT DURATION OF TOUR ALONG A DIRECTED GRAPH

GRAPH PROPERTIES

- Ca. 33000 vertices
- A vertex can be a stop on a tour for one train, but a runtrough point for another
- Some edges in the graph are used by only one type of train
- Most edges are used by multiple types of trains
- Data does not exist for all types (e.g. freight trains are missing but influence overall punctuality)
- Data cannot be expected to be correct at all times



THE AVAILABLE DATA MUST BE PREPROCESSED INTO DIGESTABLE STREAMS

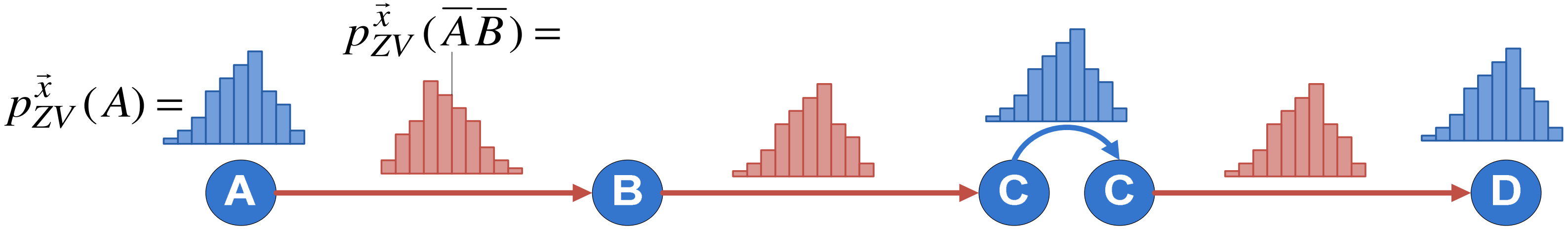
REAL-TIME MESSAGES

f_btg	f_zn	f_nr	f_fsstat	f_bstid	f_rsoll	f_ist	f_sglsid	f_iglsid	f_sstrid	t_nr
21.04.2015	883H	1	2	AK	21.04.2015 14:49	21.04.2015 14:50	103	103	1220	2
21.04.2015	883H	2	5	AMR	21.04.2015 14:53	21.04.2015 14:54	84	84	1220	3
21.04.2015	883H	3	5	AFT	21.04.2015 14:56	21.04.2015 14:56	82	82	1220	4
21.04.2015	883H	4	5	ABRD	21.04.2015 14:59	21.04.2015 14:59	601	601	1220	5

SCHEDULE DATA

lfd_nr	btg	zn	bstid	bstname	halt_lfd_nr	sollan	sollab	sglsid	istan	istab	iglsid	sstrid	unplausibel	vhalt	progan	progab	gattung
1	21.04.2015	883H	AK	Kiel Hbf	0	NULL	21.04.2015 14:49	103	NULL	NULL	103	1220	0	1	False	False	FERN
2	21.04.2015	883H	AMR	NULL	-1	21.04.2015 14:53	21.04.2015 14:53	84	NULL	NULL	84	1220	0	0	False	False	FERN
3	21.04.2015	883H	AFT	NULL	-1	21.04.2015 14:56	21.04.2015 14:56	82	NULL	NULL	82	1220	0	0	False	False	FERN
4	21.04.2015	883H	ABRD	NULL	-1	21.04.2015 14:59	21.04.2015 14:59	601	NULL	NULL	601	1220	0	0	False	False	FERN
5	21.04.2015	883H	AEF	NULL	-1	21.04.2015 15:02	21.04.2015 15:02	25BP	NULL	NULL	25BP	1220	0	0	False	False	FERN
6	21.04.2015	883H	AN G	NULL	-1	21.04.2015 15:04	21.04.2015 15:04	14	NULL	NULL	14	1220	0	0	False	False	FERN
7	21.04.2015	883H	AN	Neumünster	1	21.04.2015 15:05	21.04.2015 15:07	104	NULL	NULL	104	1220	0	1	False	False	FERN
8	21.04.2015	883H	ABRS	NULL	-1	21.04.2015 15:15	21.04.2015 15:15	202	NULL	NULL	202	1220	0	0	False	False	FERN
9	21.04.2015	883H	AWST	NULL	-1	21.04.2015 15:19	21.04.2015 15:19	2	NULL	NULL	2	1220	0	0	False	False	FERN

CORE CONCEPT: CUMMULATION OF PREDICTED ADDITIONAL DELAYS ALONG THE TRAIN TOUR



Expectation value of distributions

$$t_{pr}(D) = t_{akt} + E\left[p_{ZV}^{\vec{x}}(\Delta t_{AB})\right] + E\left[p_{ZV}^{\vec{x}}(\Delta t_{BC})\right] + E\left[p_{ZV}^{\vec{x}}(\Delta t_{CC})\right] + E\left[p_{ZV}^{\vec{x}}(\Delta t_{CD})\right]$$

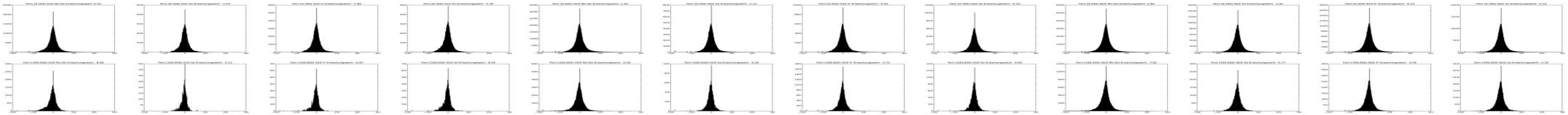
Expectation value of convoluted probablity density functions

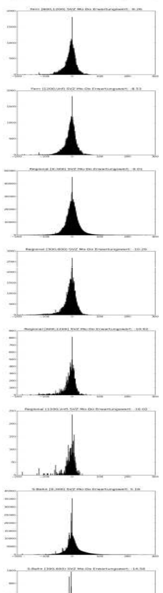
$$t_{pr}(D) = t_{akt} + E\left[\left(\left(p_{ZV}^{\vec{x}}(\Delta t_{AB}) * p_{ZV}^{\vec{x}}(\Delta t_{BC})\right) * p_{ZV}^{\vec{x}}(\Delta t_{CC})\right) * p_{ZV}^{\vec{x}}(\Delta t_{CD})\right]$$

Sum of local predictions of artificial neural network

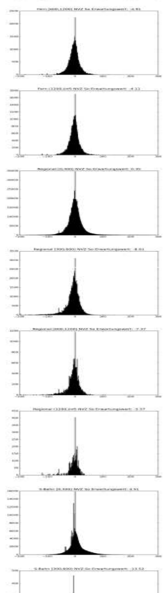
$$t_{pr}(D) = t_{akt} + f_{AB}(\vec{x}) + f_{BC}(\vec{x}) + f_{CC}(\vec{x}) + f_{CD}(\vec{x})$$

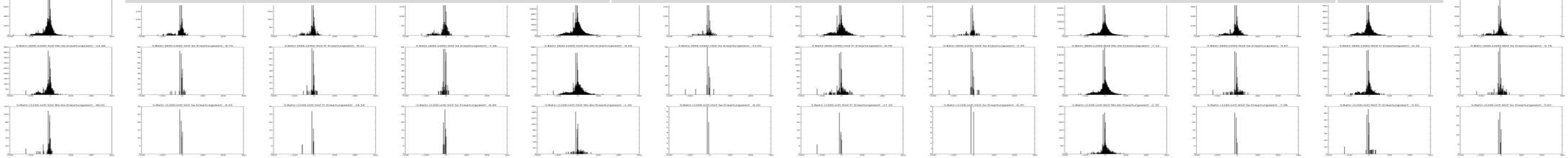
MODEL FOR NON LEARNING APPROACH: VERTEX SPECIFIC HISTORGRAMS





Feature Categories	X_i	#
Type of vessel	A, B, C	3
Time of day	HVZ (7-9, 15-18), NVZ (9-15,18-22), SVZ (22-7)	3
Type of Day	Mo-Do, Fr+Tage vor Feiertag, Sa, So+Feiertage	4
Current train delay	<5min, 5-10min, 10-20min,>20min	4





THE PROBLEMS OF THE „CLASSICAL“ APPROACHES LEAD TO WEAK PREDICTIONS

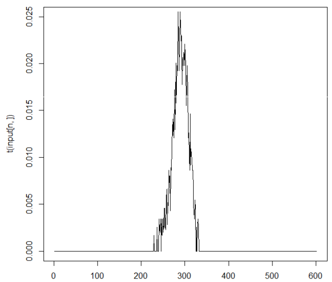
TODAY’S SOLUTION

- Linear extrapolation of current delay spiced with known events (sometimes)
- Data is not always accurate due to manual intervention
- Completely agnostic w.r.t. already known information, e.g. type of vessel, time of day, ...

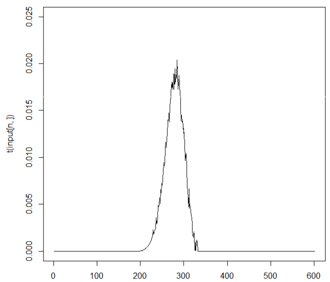
CONVOLUTION OF PDF’S

- For some segments the PDF’s are not very “smooth”
- Even for smaller tours, the PDF’s for tour segments far in the future are very wide => Low p for point estimation

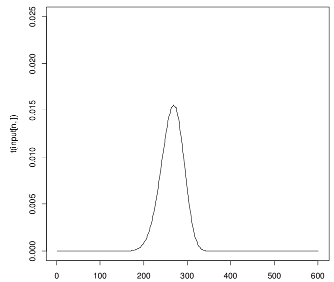
$$(f * g)(n) = \sum_{m=-M}^{M} f(n-m)\, g(m)$$



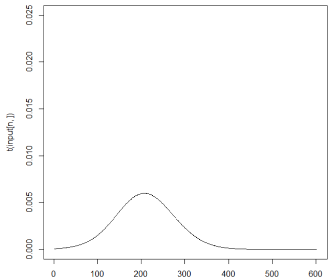
n = 1



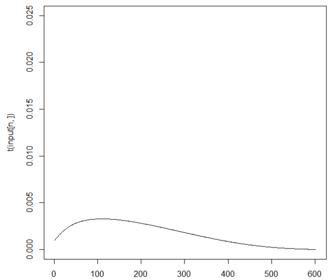
n=2



n = 3

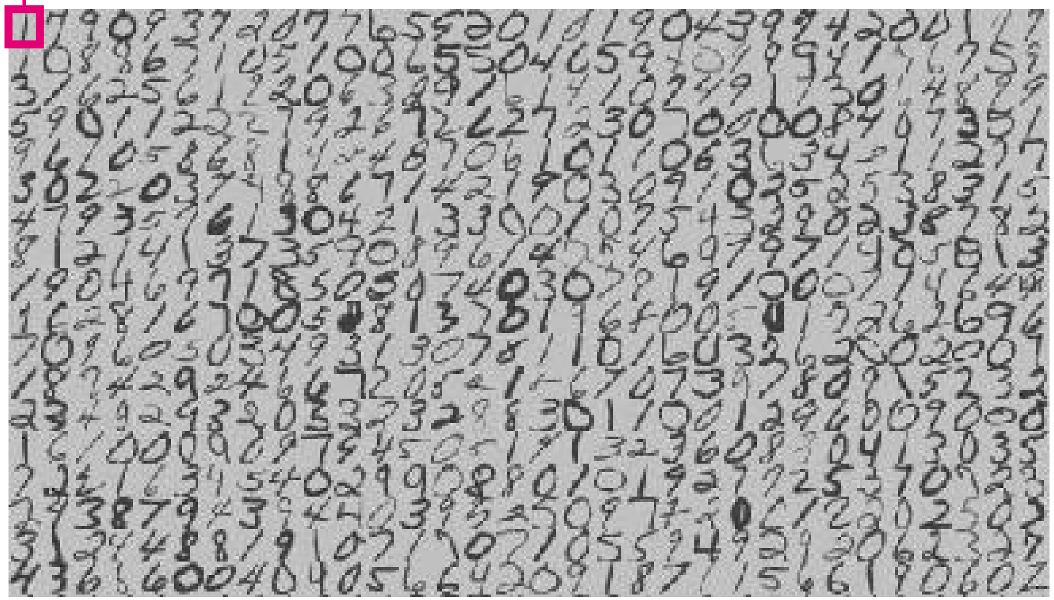


n = 20



n = 150

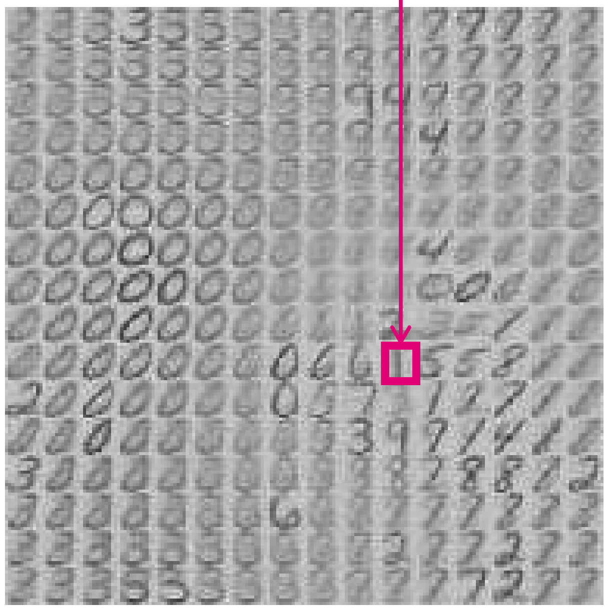
VISUALIZING CLUSTERS OF INFORMATION WITH SELF-ORGANIZING FEATURE MAPS



Input Space

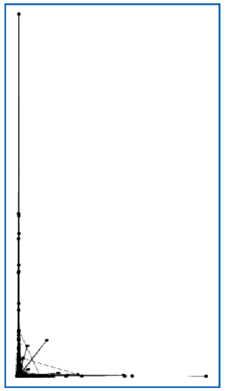
SOFMs are

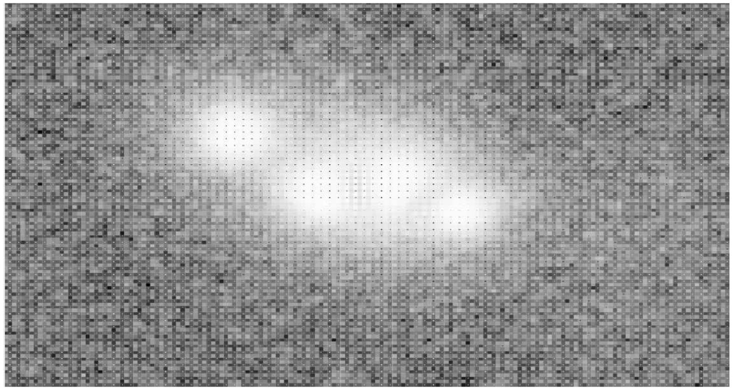
- dimension-reducing
- piecewise connected
- nonlinear-mapping
- topology-preserving
- variable resolution

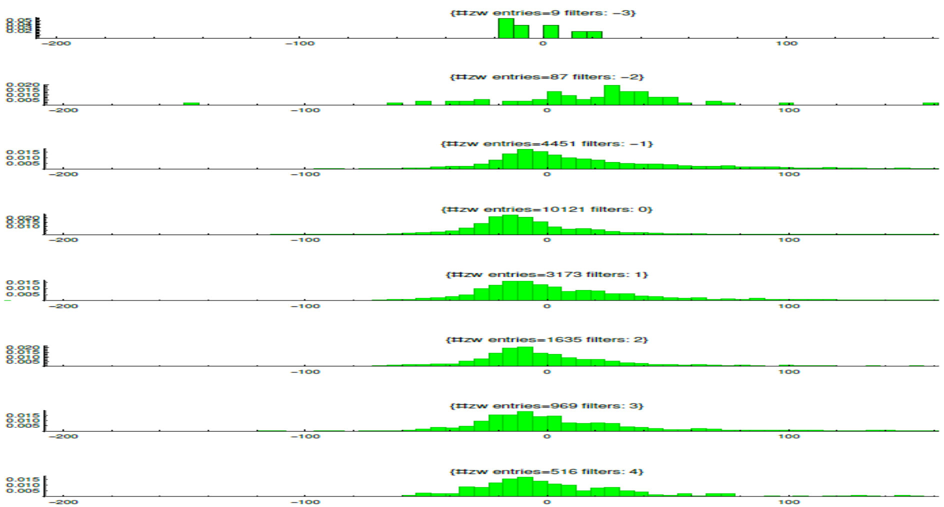


Output Space

CLUSTERING SHOWS THAT INCREASE OF DELAY IS NOT CLEARLY SEPARABLE BETWEEN DIFFERENT CLUSTERS



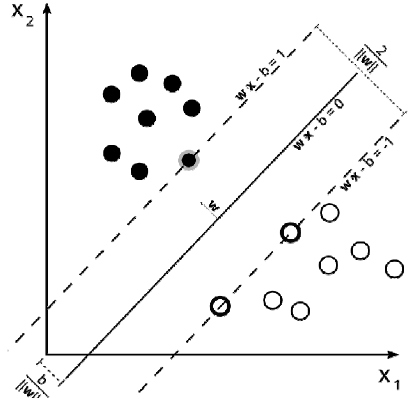




USING SUPERVISED AND NON-SUPERVISED ALGORITHMS

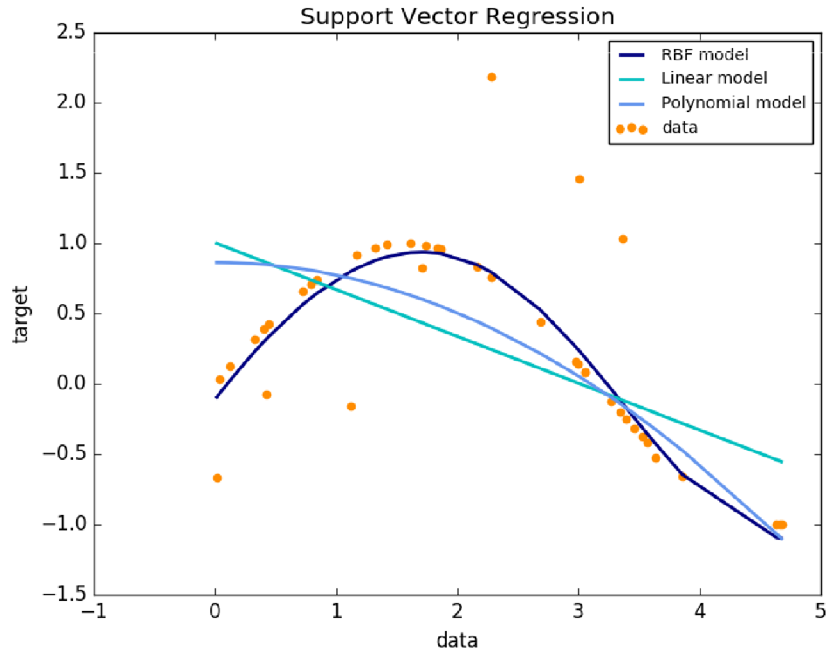
- Optimization of feature categories with unsupervised learning (Self-Organizing Map, k-Means) on different vertices
    - No clear clustering (in terms of feature to detect) with currently available features
    - No usable predictions
- Supervised learning using the existing features provides much better predictions
    - Support Vector Machines (SVM)

SUPERVISED LEARNING APPOACH: NON-LINEAR REGRESSION USING A SUPPORT VECTOR MACHINE



SVM PROPERTIES

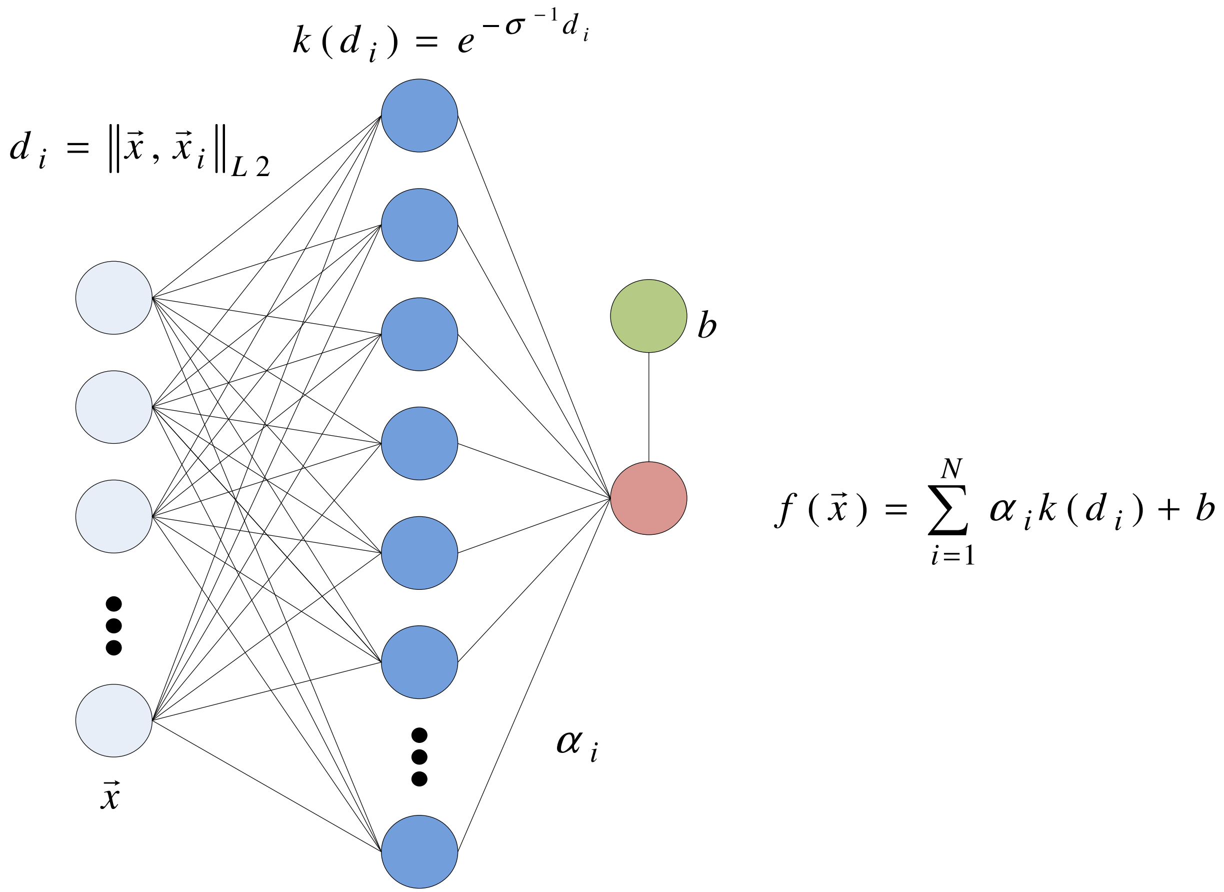
- Finds optimal separating hyperplane in high-dimensional space
- Automatically prunes the number of support vectors needed
- Uses “kernel trick” to make sets separable by transforming the data to higher dimension
- Training is basically an quadratic optimization problem
- svms have found widespread use in classification and prediction



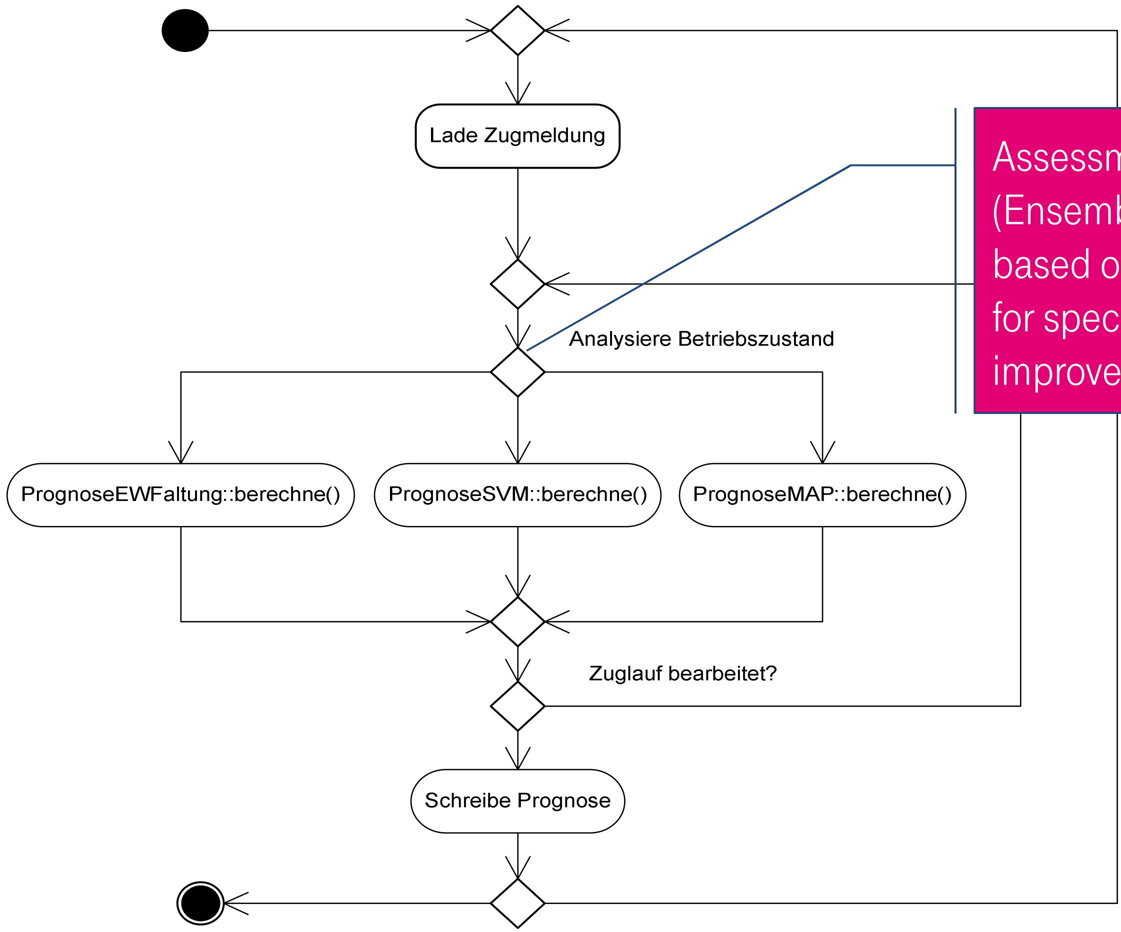
THE NEURAL NETWORKS ARE TRAINED WITH A VARIABLE SET OF INPUT PARAMETERS IN A HIGHLY PARALLELIZED APPROACH

TRAINING OF SVM

- Vertex specific training, i.e. one aNN per vertex
- Highly parallelizable on existing cluster – due to independence of vertices
- Performance: 22000 aNNs in 33 min
- Target value: additional delay



THE DESIGN OF THE SOFTWARE ENABLES THE ONLINE SELECTION OF THE BEST PERFORMING ALGORITHM - ENSEMBLING



Assessment of operational mode: (Ensemble Method): dynamic selection based on the performance of the algorithms for specific operational states (continuously improved)

IMPROVEMENT OF PREDICTION BY WEIGHTING OF HISTORICAL DATA

YOUNGER DATA IS MORE IMPORTANT

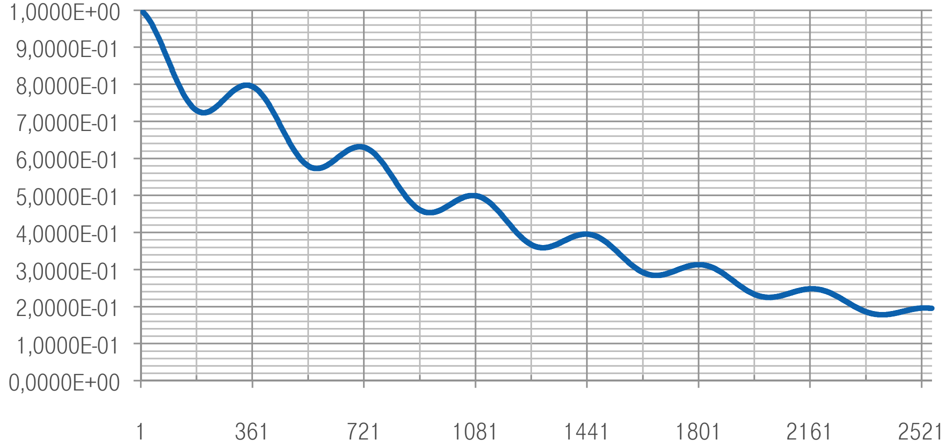
- Heigher weight on more current data, e.g. construction work
- Reduction of influence of older situations
- Consideration of seasonality („last july is more important than last september“)

REALIZATION

- Standard approach: exponential filtering
  - Does not take seasonality into account
- Approach: modulate exponential filtering with periodical function

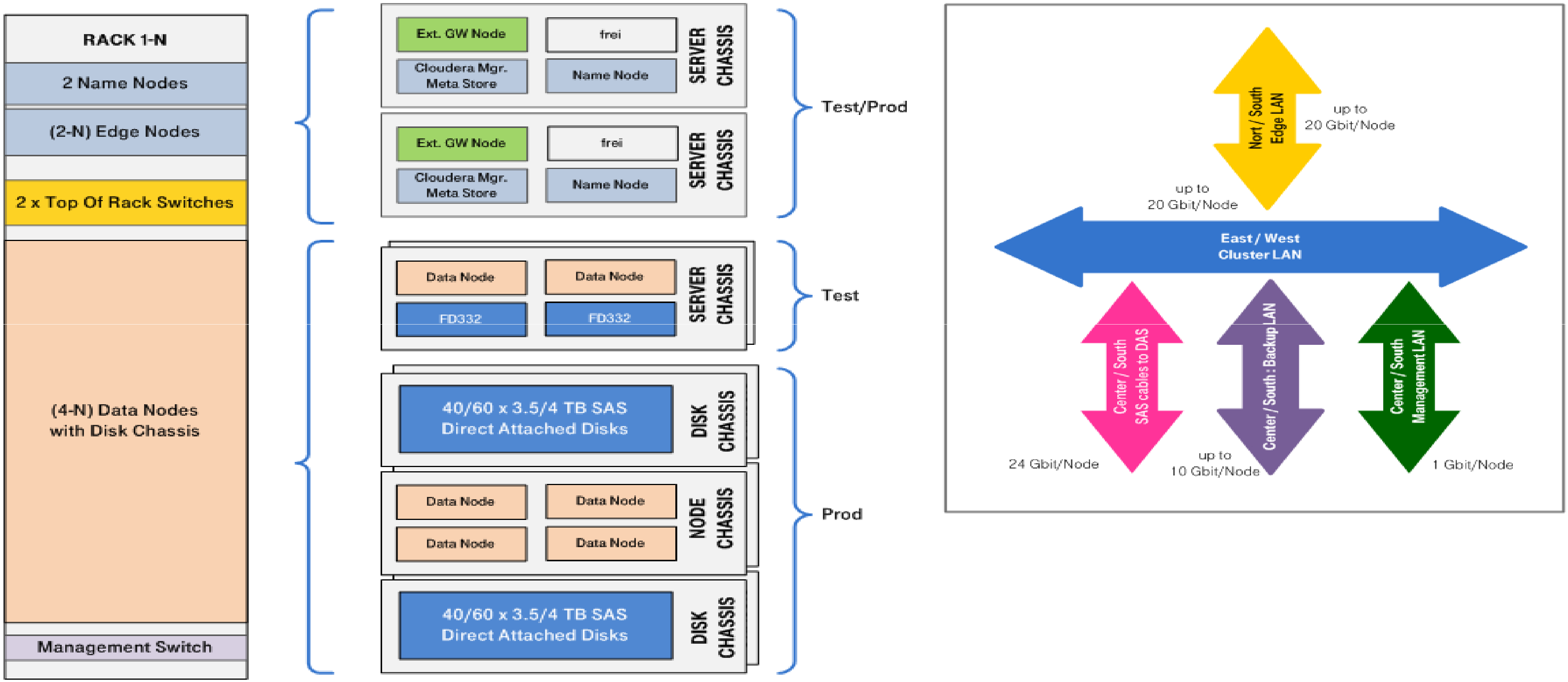
$$f(t) = \alpha \cdot (1-\alpha)^n \cdot (\eta + \cos(\frac{n}{182.5} \cdot \pi)) \cdot f(0)^{-1}$$

SEASONALIZATION WITH EXPONENTIAL FILTERING



ARCHITECTURE

DATA PLATFORM SYSTEM ARCHITECTURE

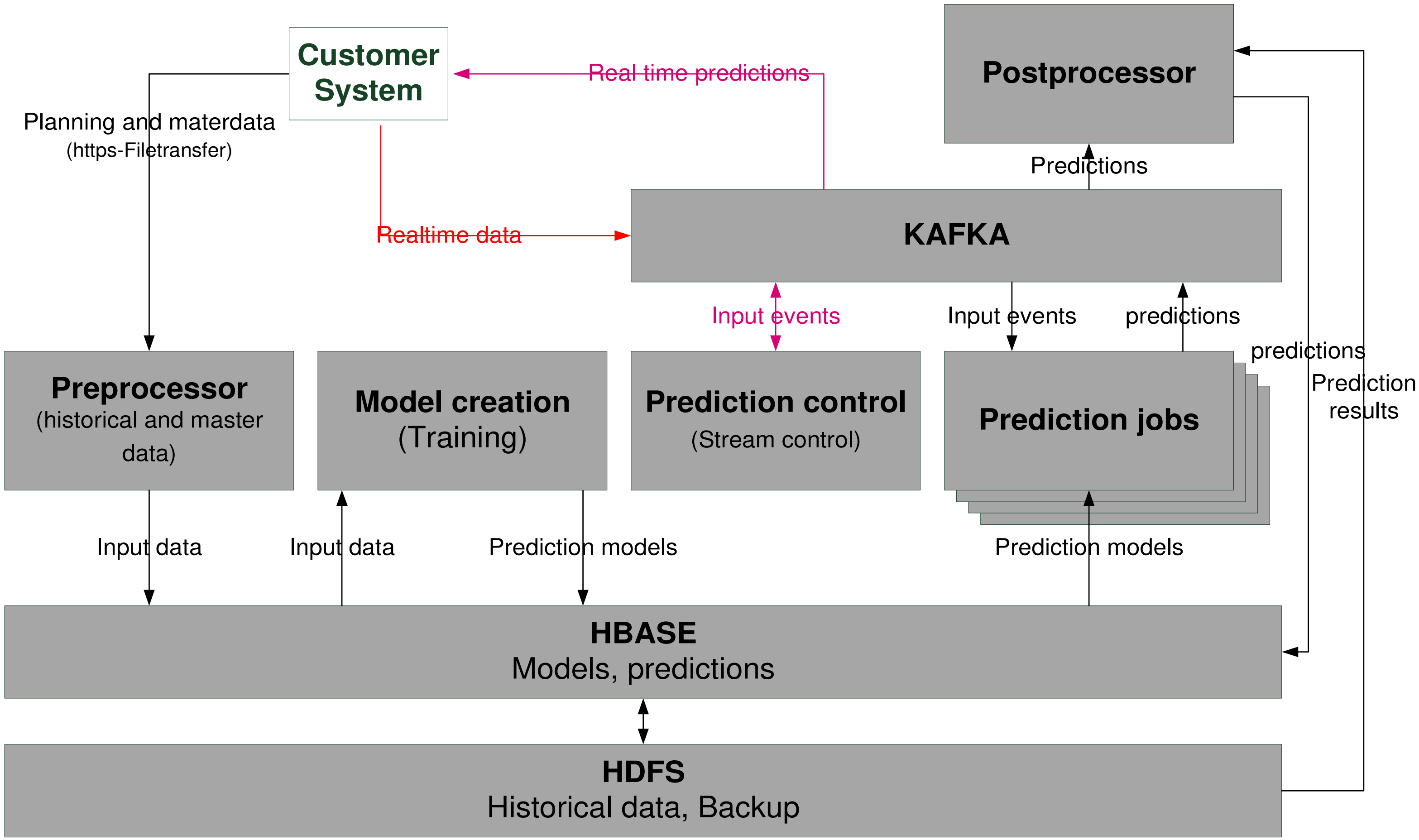


OUR PLATFORM SCALES FROM 3 TO 2400 DATA NODES

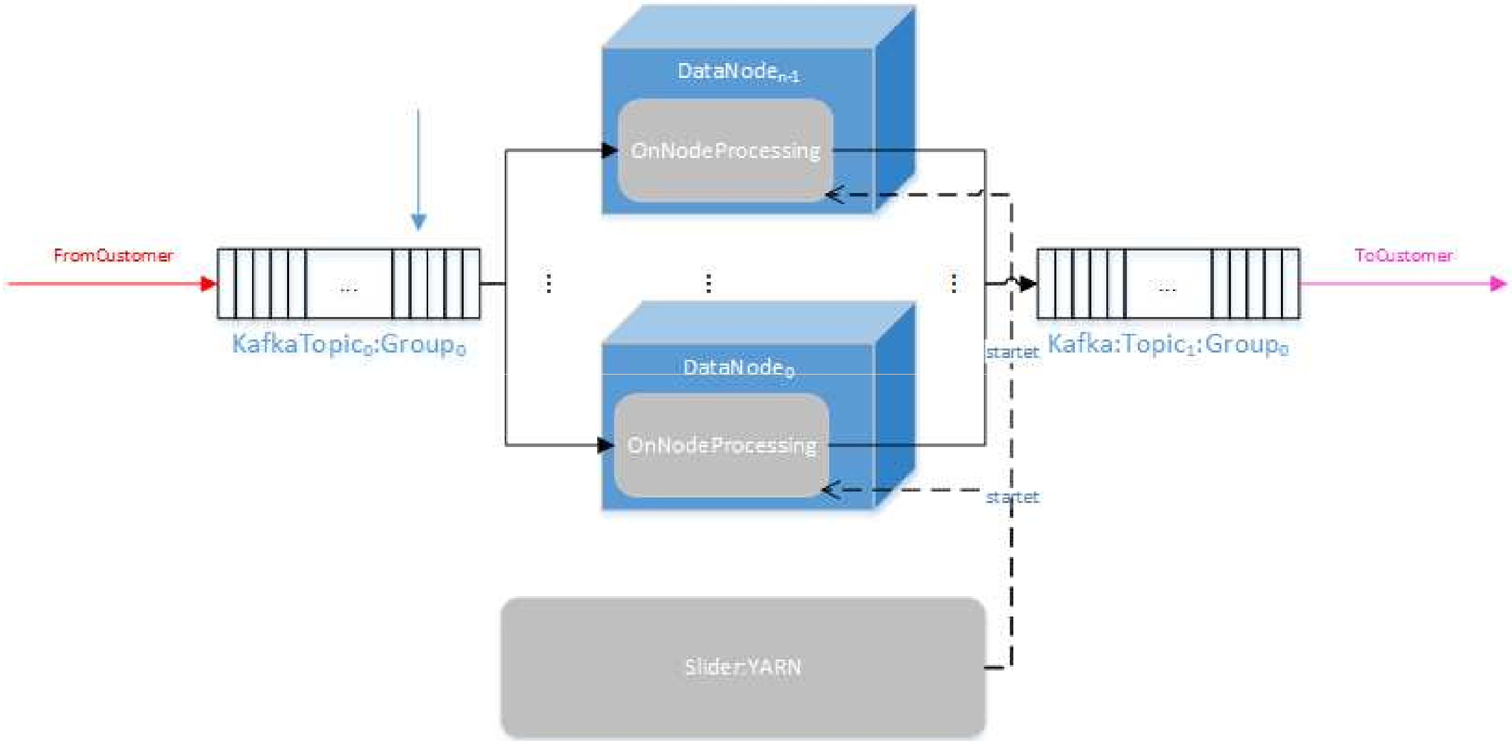
Function	Master & Name Node	Kafka (I/O) Node	Data Node
Hardware	Intel x86		
OS	Linux 64 bit		
CPU	2x Intel Xeon E5-2620 v4 (8 Cores, 20MB Cache)		
RAM	256 GB		
Storage	2 x 2 TB		15 x 4 (8) TB

- 2x10 Gbit/s ToR switches in fabric mode
- >20GBit/s I/O bandwitdth/data node
- Scalable per Rack up to 50 nodes

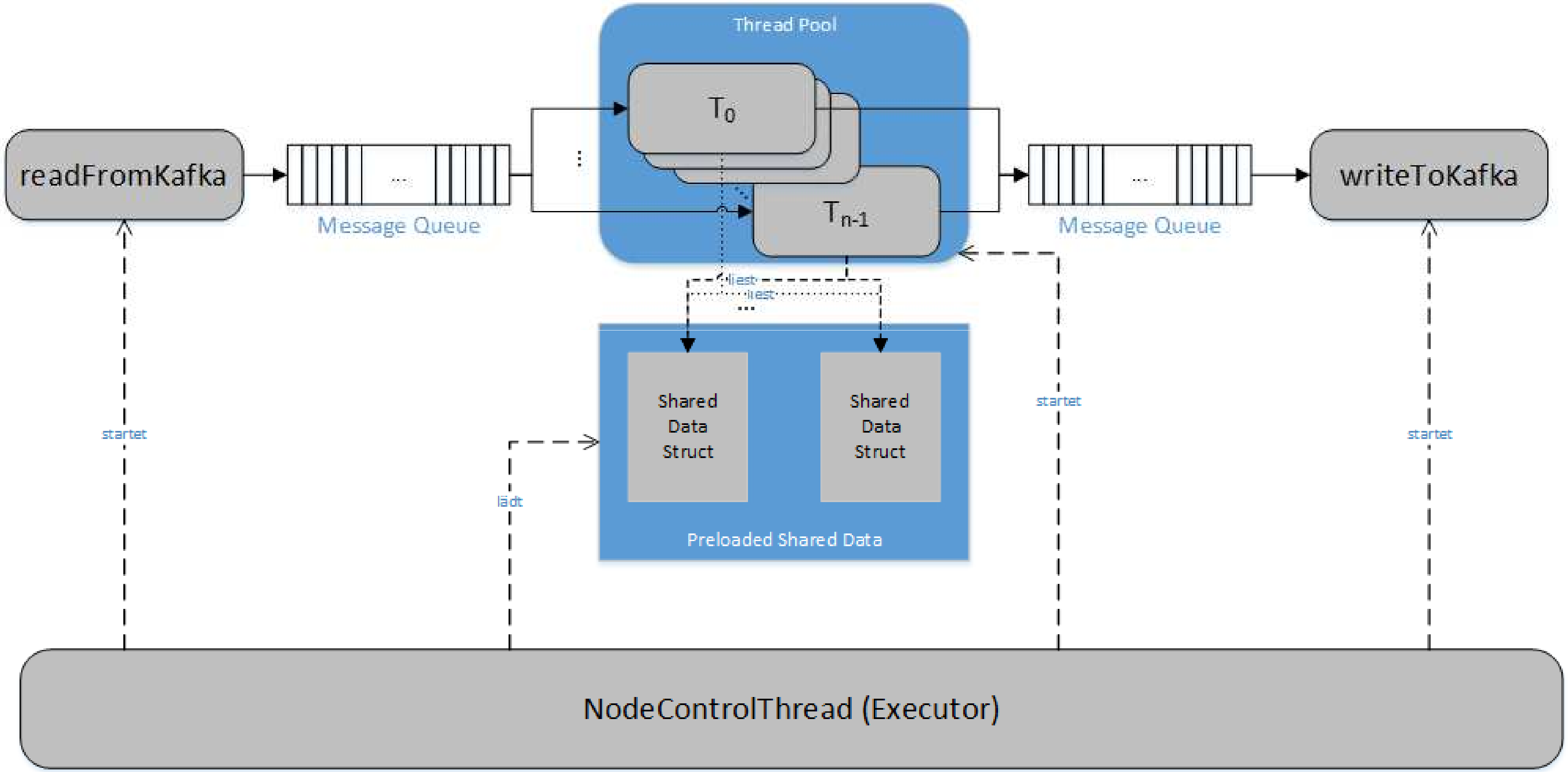
THE TARGET ARCHITECTURE CAN BE FLEXIBLY USED FOR DIFFERENT USE CASES



THE ARCHITECTURE USES THE MINIMAL POSSIBLE SET OF FRAMEWORKS TO IMPLEMENT A FARMER WORKER PATTERN

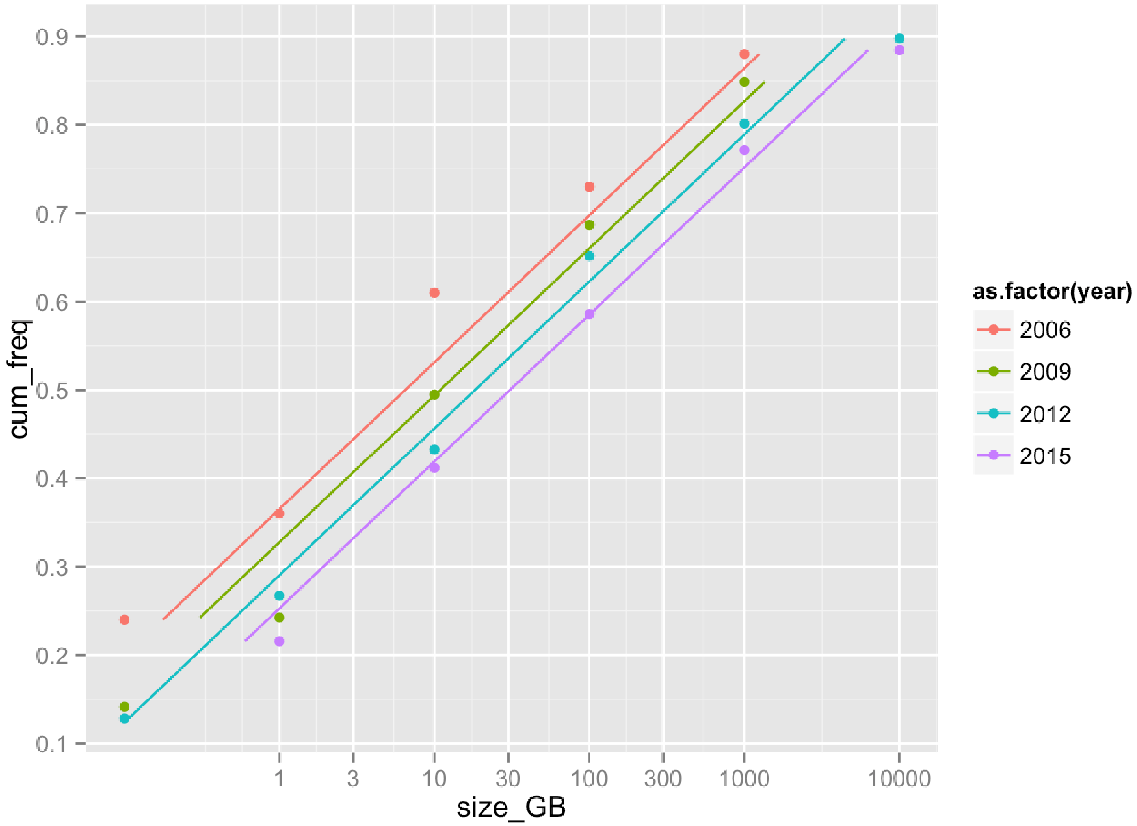


EACH NODE REPEATS THE FARMER WORKER PATTERN. IN-MEMORY COMPUTING SPEEDS UP PERFORMANCE.



TRENDS IN DATA ANALYTICS AND MACHINE LEARNING FROM A COMPUTING PERSPECTIVE

FAST DATA EATS BIG DATA



source: https://github.com/szilard/dataset-sizes-kdnuggets

GROWTH RATE IN RAM EXCEEDS GROWTH RATE IN DATA

- Data Node C4 (2013: 32 GiB)
- Data Node DB (2016: 256 GiB)

- RAM Growth/a: 71%
- Data Growth/a: 20%

REAL-TIME PROCESSING BECOMES REALITY

NEW (OLD) DATATYPES ENABLE IN-MEMORY COMPUTING – FP16 (IEEE 754-2008 STANDARDIZED)

FP16 PROPERTIES

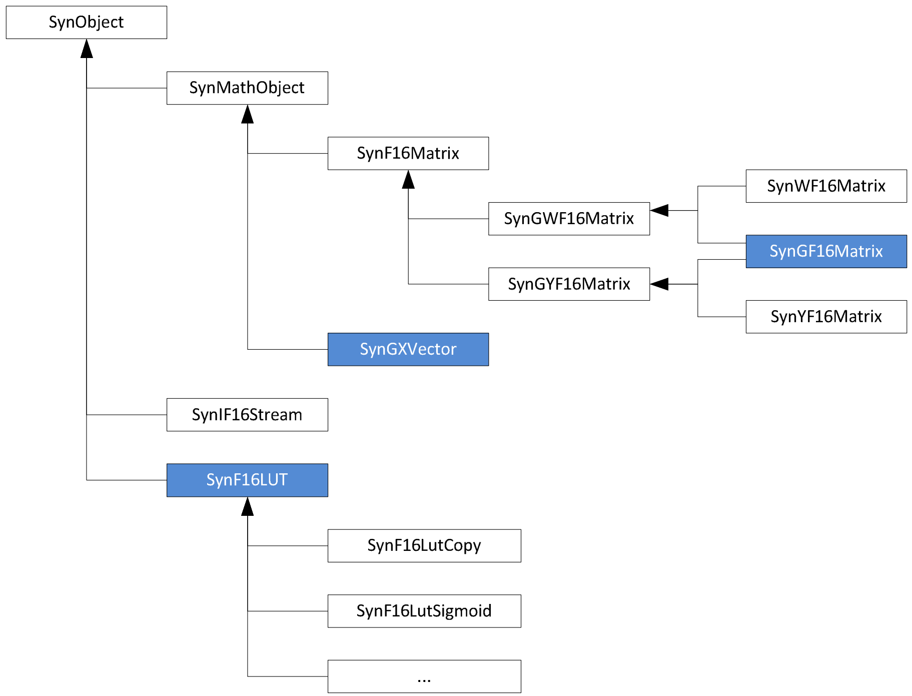
- 16 bit "binary16"
- 10 bit mantissa, 5 bit exponent (+/- 65504.0)
- Originally only intended for storage, not for computation
- Support in x86 since IvyBridge "`__m128 _mm_cvtph_ps (__m128i a)`"
- Now computations are also available in GPU (since nVidia „Pascal")
- OpenCL as flexible programming framework
- And people tend repeat the errors from the past (SysArr) (arXiv:1502.02551v1 [cs.LG] 9 Feb 2015)

BUT SIMILAR APPROACHES EXISTED ALREADY 25 YEARS AGO

- Most Neural Networks are fine with 16bit floats! (and so are many ML algos)
- We had 16bit fixed point computations
    - DSPs (e.g. Motorola 56k)
    - Dedicated Neurocomputers (Synapse1)
    - Neurocoprocessors (Synapse3•PC) with hardware-independent programming framework – also auto scaling (Systolic Array)

FROM A MACHINE LEARNING POV FP16 SHOULD BECOME A STANDARD TYPE

FLASHBACK FROM THE PAST: SYNUSE•BASE DATATYPES WERE COMPLETELY HARDWARE AGNOSTIC



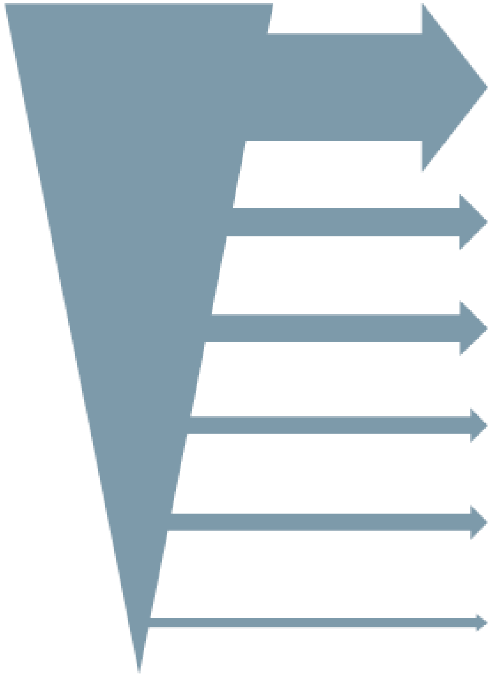
FP16 WHISHLIST: FULL HARDWARE INDEPENDENT SUPPORT

- Type support in common languages
  - `short float`, `float`, `double`, `long double`
- Compute support in standard cpu
  - X86 via AVX(2) intrinsics
  - ARM via NEON (>8.2)
  - ...but not out of the (C++)-box
- Opaque transformation into GPU instructions
  - OpenCL (only for storage via extension)
  - CUDA?

FOMITCHEV, ET. AL: „ ADDING FUNDAMENTAL TYPE FOR SHORT FLOAT"

ONLY 1% OF DATA ON OFFSHORE LOCATIONS CAN BE USED REMOTELY

100%
~30,000 sensors gathering data

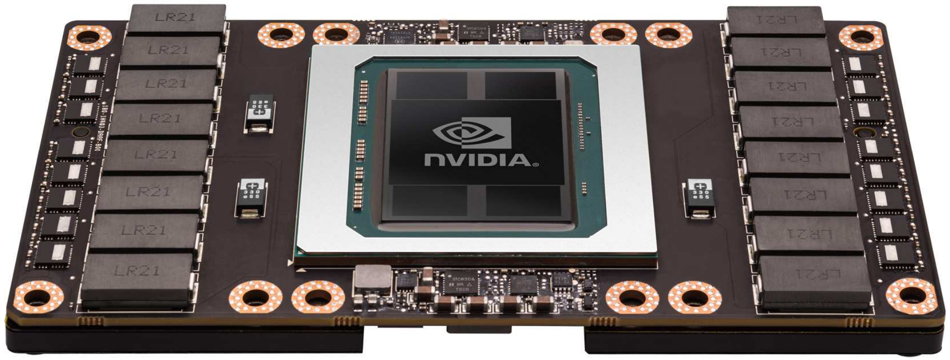


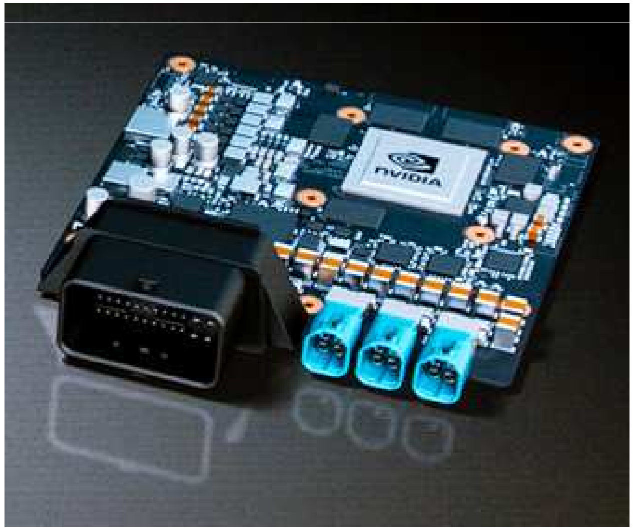
Data capture	~40% of all data is never stored; remainder is stored locally offshore
Infrastructure	Only ~1% of data can be streamed onshore for daily use
Data management	Data cannot be accessed in real time, enabling only “ad hoc” analysis
Analytics	Reporting is limited to a few metrics, which are monitored in retrospect
Deployment	No interface is in place to enable real-time analytics to capture offshore data
People and processes	Maintenance is still conducted at manufacturer-recommended intervals

<1%
of data used for decision making

SOURCE: McKinsey Global Institute analysis

EDGE COMPUTING IS COMMODITY AND NECESSITY

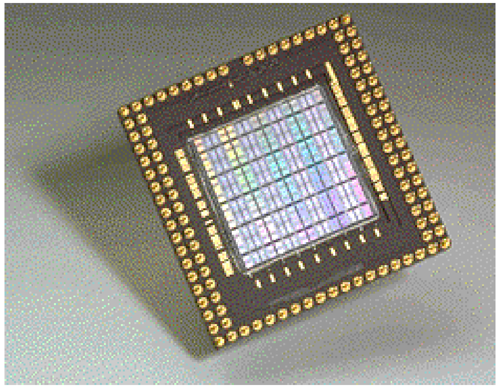


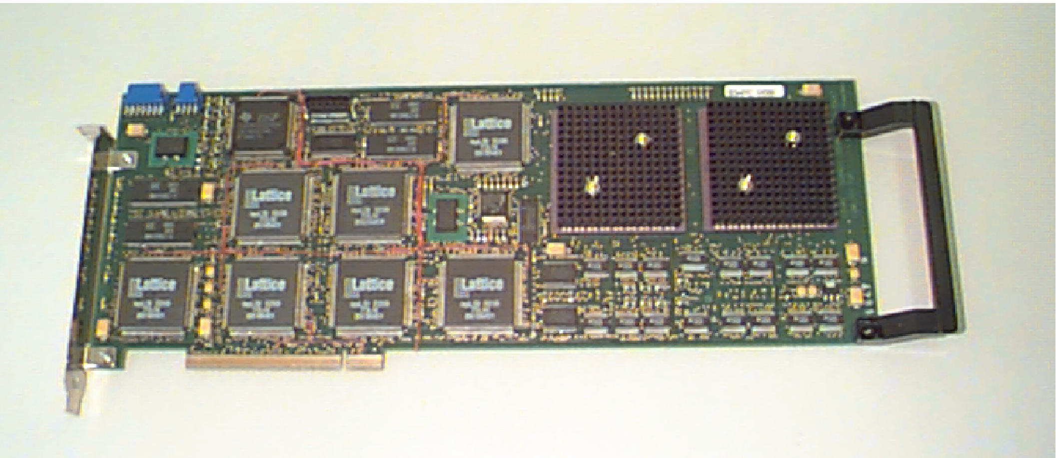


LOCAL ENTITIES GENERATE TOO MUCH DATA TO BE TRANSPORTED TO CENTRAL LOCATIONS

- An autonomous car is expected to produce 1TiB/h
- Full data set required to provide service
- Only partial data set needed for central processing/central services
- Edge nodes provide local service plus filtering for transport to backend (20TOPS DL@20W)

GPU IS HERE TO STAY – ALL OTHERS WILL GO THE WAY OF THE DODO





THE PAST HAS SHOWN, THAT HIGHLY SPECIALIZED CARDS DO NOT GAIN ENOUGH MARKET SHARE TO SURVIVE

- Wo still knows
  - CNAPS
  - Synapse (OK, now you know a little)
  - Intel Ni 1000
  - Intel ETANN (80170NX)
  - ...
- But we still have
  - X86
  - POWER
  - ARM
  - ... all now with multicore

THANK YOU!