Architecting Parallel Software with Patterns

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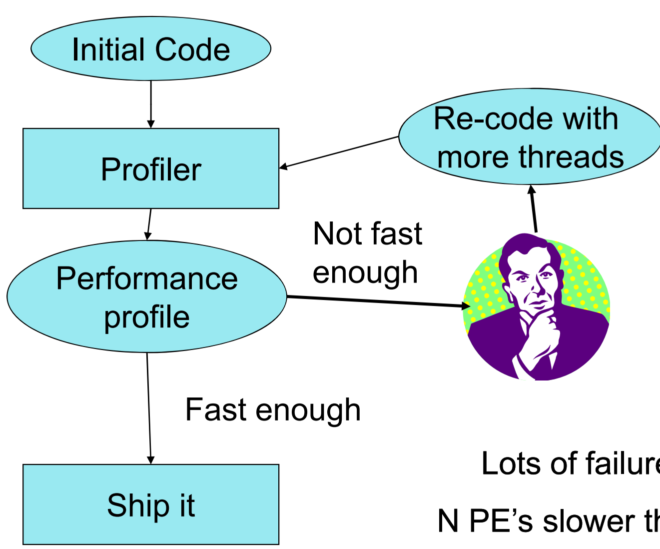
with thanks to Tim Mattson

Assumption #1: How **not** to develop parallel code



Lots of failures

N PE's slower than 1

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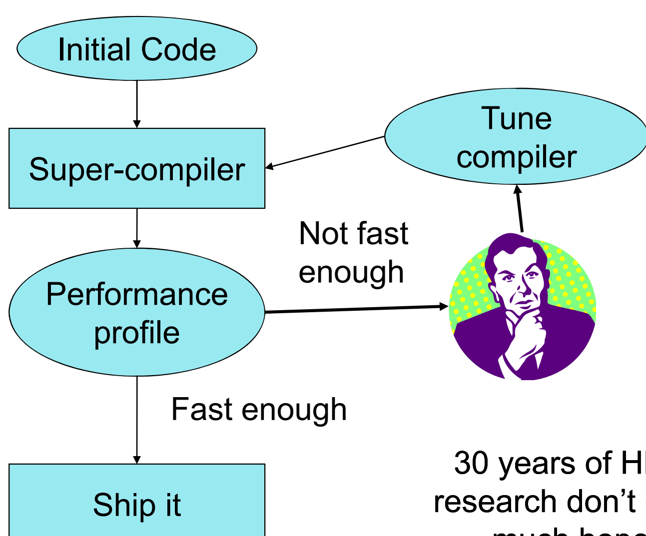
Steiner Tree Construction Time By Routing Each Net in Parallel

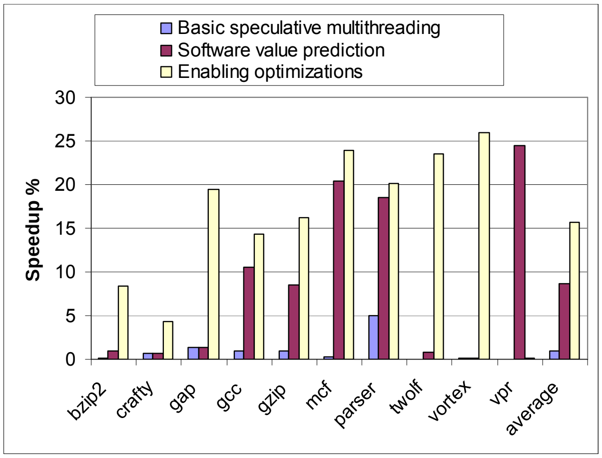
Benchmark	Serial	2 Threads	3 Threads	4 Threads	5 Threads	6 Threads
adaptec1	1.68	1.68	1.70	1.69	1.69	1.69
newblue1	1.80	1.80	1.81	1.81	1.81	1.82
newblue2	2.60	2.60	2.62	2.62	2.62	2.61
adaptec2	1.87	1.86	1.87	1.88	1.88	1.88
adaptec3	3.32	3.33	3.34	3.34	3.34	3.34
adaptec4	3.20	3.20	3.21	3.21	3.21	3.21
adaptec5	4.91	4.90	4.92	4.92	4.92	4.92
newblue3	2.54	2.55	2.55	2.55	2.55	2.55
average	1.00	1.0011	1.0044	1.0049	1.0046	1.0046

Assumption #2: Nor this



30 years of HPC research don't offer much hope

Automatic parallelization?



- Aggressive techniques such as speculative multithreading help, but they are not enough.
- Ave SPECint speedup of 8% … will climb to ave. of 15% once their system is fully enabled.
- There are no indications auto par. will radically improve any time soon.
- Hence, I do not believe Auto-par will solve our problems.

Results for a simulated dual core platform configured as a main core and a core for speculative execution.

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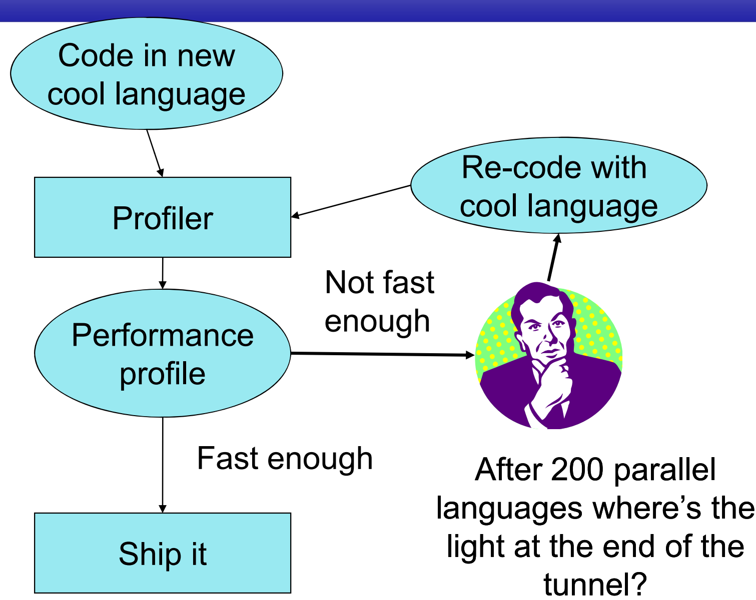
Assumption #3: This won't help either



Parallel Programming environments in the 90's

ABCPL	CORRELATE	GLU	Mentat	Parafrase2	pC++
ACE	CPS	GUARD	Legion	Paralation	SCHEDULE
ACT++	CRL	HAsL.	Meta Chaos	Parallel-C++	SciTL
Active messages	CSP	Haskell	Midway	Parallaxis	POET
Adl	Cthreads	HPC++	Millipede	ParC	SDDA.
Adsmith	CUMULVS	JAVAR.	CparPar	ParLib++	SHMEM
ADDAP	DAGGER	HORUS	Mirage	ParLin	SIMPLE
AFAPI	DAPPLE	HPC	MpC	Parmacs	Sina
ALWAN	Data Parallel C	IMPACT	MOSIX	Parti	SISAL.
AM	DC++	ISIS.	Modula-P	pC	distributed smalltalk
AMDC	DCE++	JAVAR	Modula-2*	pC++	SMI.
AppLeS	DDD	JADE	Multipol	PCN	SONiC
Amoeba	DICE.	Java RMI	MPI	PCP:	Split-C.
ARTS	DIPC	javaPG	MPC++	PH	SR
Athapascan-0b	DOLIB	JavaSpace	Munin	PEACE	Sthreads
Aurora	DOME	JIDL	Nano-Threads	PCU	Strand.
Automap	DOSMOS.	Joyce	NESL	PET	SUIF.
bb_threads	DRL	Khoros	NetClasses++	PETSc	Synergy
Blaze	DSM-Threads	Karma	Nexus	PENNY	Telegrphos
BSP	Ease .	KOAN/Fortran-S	Nimrod	Phosphorus	SuperPascal
BlockComm	ECO	LAM	NOW	POET.	TCGMSG.
C*.	Eiffel	Lilac	Objective Linda	Polaris	Threads.h++.
"C* in C	Eilean	Linda	Occam	POOMA	TreadMarks
C**	Emerald	JADA	Omega	POOL-T	TRAPPER
CarlOS	EPL	WWWinda	OpenMP	PRESTO	uC++
Cashmere	Excalibur	ISETL-Linda	Orca	P-RIO	UNITY
C4	Express	ParLin	OOF90	Prospero	UC
CC++	Falcon	Eilean	P++	Proteus	V
Chu	Filaments	P4-Linda	P3L	QPC++	ViC*
Charlotte	FM	Glenda	p4-Linda	PVM	Visifold V-NUS
Charm	FLASH	POSYBL	Pablo	PSI	VPE
Charm++	The FORCE	Objective-Linda	PADE	PSDM	Win32 threads
Cid	Fork	LiPS	PADRE	Quake	WinPar
Cilk	Fortran-M	Locust	Panda	Quark	WWWinda
CM-Fortran	FX	Lparx	Papers	Quick Threads	XENOOPS
Converse	GA	Lucid	AFAPI.	Sage++	XPC
Code	GAMMA	Maisie	Para++	SCANDAL	Zounds
COOL	Glenda	Manifold	Paradigm	SAM	ZPL

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So What's the Alternative?

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Principles of SW Design

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- After 15 years in industry, at one time overseeing the techology of 25 software products, my two best principles to facilitate good software design are:
  - Use of modularity
  - Definition of invariants
- Modularity helps:
  - Architect: Makes overall design sound and comprehensible
  - Project manager:
    - As a manager I am able to comfortably assign different modules to different developers
    - I am also able to use module definitions to track development
  - Module implementors: As a module implementor I am able to focus on the implementation, optimization, and verification of my module with a minimum of concern about the rest of the design
  - Identify invariants and key computations

Non-Principles of SW Design

- What's life like without modularity?
  - Spaghetti code
  - Wars over the interpretation of the specification
  - Waiting on other coders
  - Wondering why you didn't touch anything and now your code broke
  - Hard to verify your code in isolation, and therefore hard to optimize
  - Hard to parallelize without identifying key computations

  - Modularity will help us obviate all these
  - Parnas, "On the criteria to be used on composing systems into modules," CACM, December 1972.

Modularity is important …. But …

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Pop quiz: Is software more like?

a) A building **b) A factory**

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What computations we do is as important than how we do them ….

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Apps / Dwarves	Embed	SPEC	DB	Games	ML	HPC	CAD	Health	Image	Speech	Music	Browser
Graph Algorithms												
Graphical Models												
Backtrack / B&B												
Finite State Mach.												
Circuits												
Dynamic Prog.												
Unstructured Grid												
Structured Grid												
Dense Matrix												
Sparse Matrix												
Spectral (FFT)												
Monte Carlo												
N-Body												

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Architecting Parallel Software

- Putting computation and structure together:
  - We believe the key to productively building efficient and correct parallel software is *software architecture*
- *A software architecture* is a hierarchical composition of:
  - Computational patterns – the atoms
  - Structural patterns – the molecular bonds
- This software architecture naturally gives:
  - Modularity
    - Efficient management
    - Efficient implementation
    - Efficient verification
  - Identifies key computations, invariants, and interfaces

Outline

PAMAS

- Architecting Parallel Software
- Structural Patterns
- Computational Patterns
- Examples
- Summary

Identify the SW Structure

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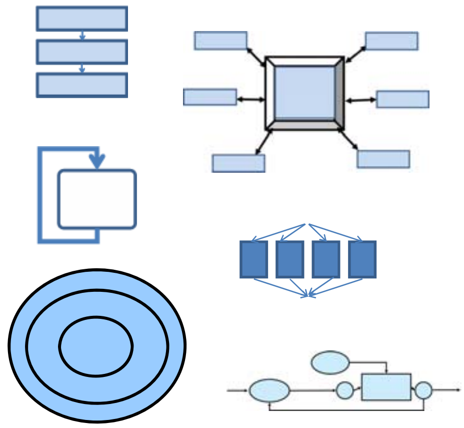
Structural Patterns

- Pipe-and-Filter
- Agent-and-Repository
- Event-based
- Layered Systems
- Model-view-controller
- Arbitrary Task Graphs
- Puppeteer
- Iterator/BSP
- MapReduce



These define the structure of our software but they *do not describe* what is computed

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Analogy: Layout of Factory Plant

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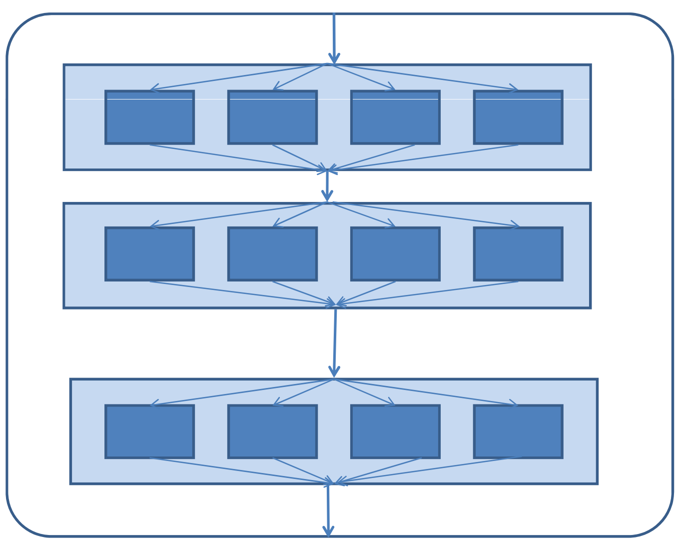

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Identify Key Computations

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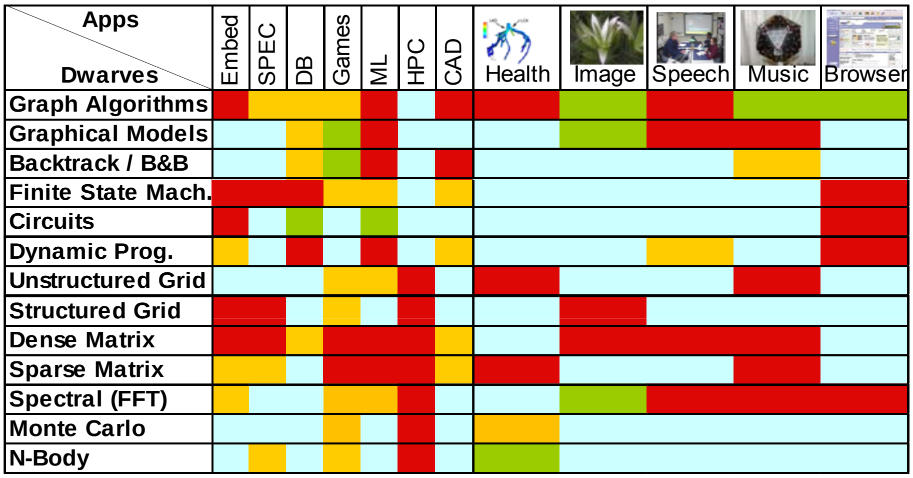

- Computational patterns describe the key computations but not how they are implemented

Analogy: Machinery of the Factory

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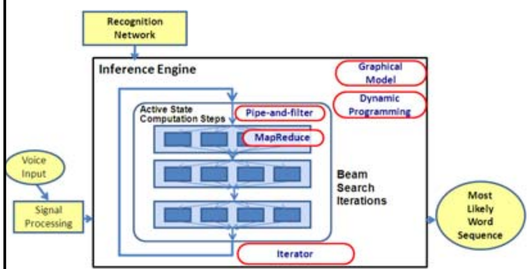
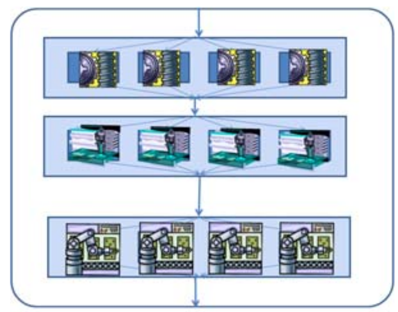
Architecting the Whole Application



- SW Architecture of Large-Vocabulary Continuous Speech Recognition



Analogous to the design of an entire manufacturing plant

- Raises appropriate issues like scheduling, latency, throughput, workflow, resource management, capacity etc.

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Outline

- Architecting Parallel Software
- → Structural Patterns
  - Pipe and filter
  - Iterator
  - Map Reduce
- Computational Patterns
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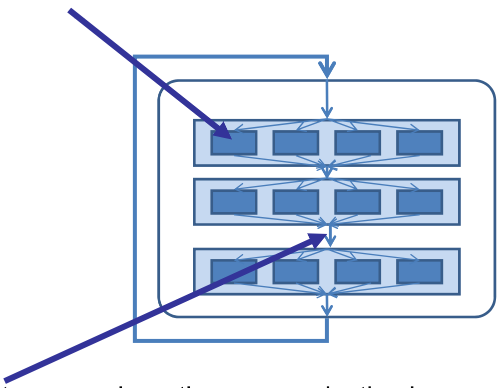
Elements of a structural pattern

- Components are where the computation happens



Connectors are where the communication happens

- A configuration is a graph of components (vertices) and connectors (edges)
- A structural patterns may be described as a familiy of graphs.

Inventory of Structural Patterns

- Pipe-and-Filter
- Agent-and-Repository
- Event-based
- Layered Systems
- Model-view-controller
- Arbitrary Task Graphs
- Puppeteer
- Iterator/BSP
- MapReduce

- We build arbitrarily complex software structures out of these nine patterns

Pattern 1: Pipe and Filter

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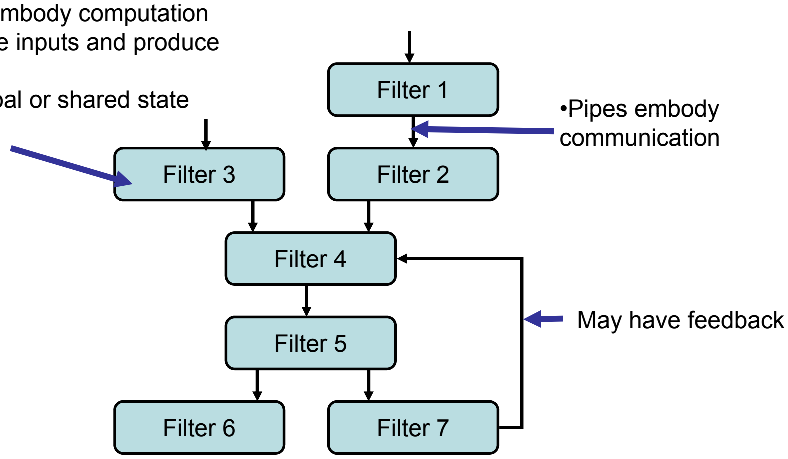
•Filters embody computation
•Only see inputs and produce outputs
• No global or shared state



Examples?

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Examples of pipe and filter

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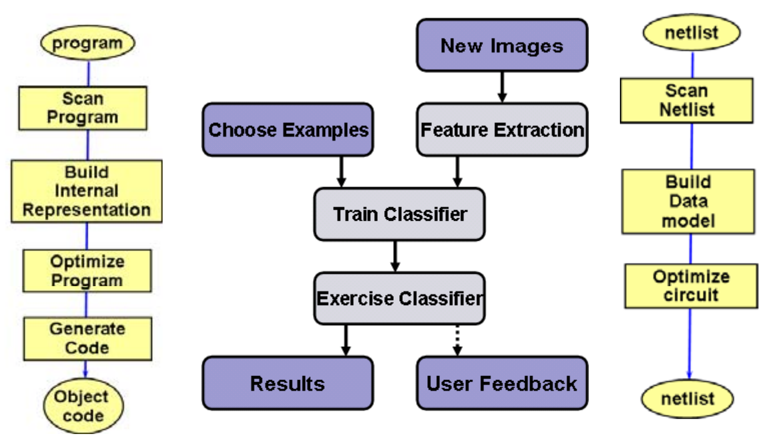
- Almost every large software program has a pipe and filter structure at the highest level



Compiler   Image Retrieval System   Logic optimizer

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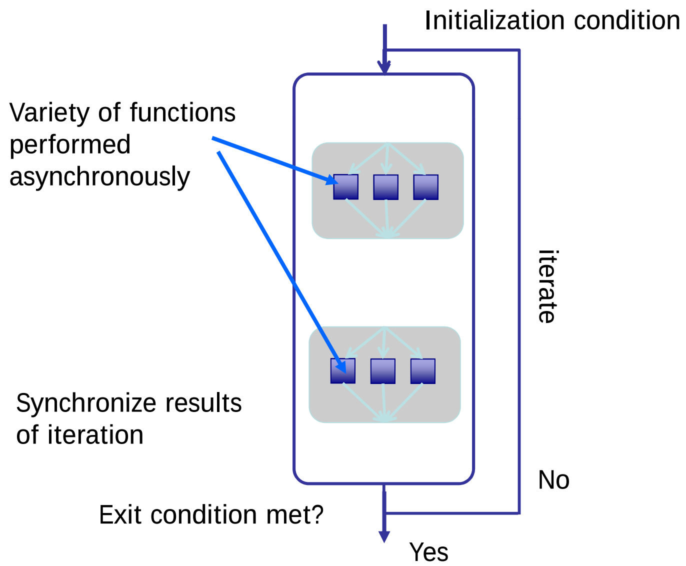
Pattern 2: Iterator Pattern



Examples?

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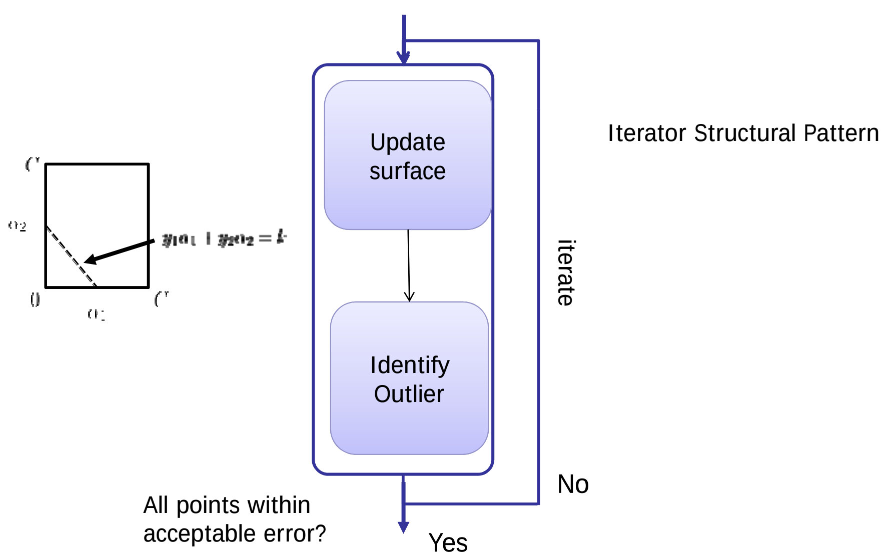
Example of Iterator Pattern: Training a Classifier: SVM Training



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Pattern 3: MapReduce

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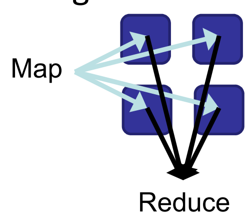
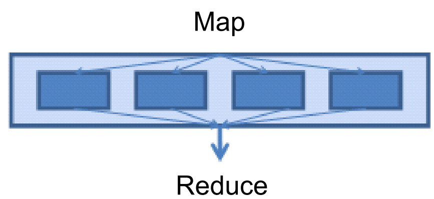
- To us, it means
  - A map stage, where data is mapped onto independent computations
  - A reduce stage, where the results of the map stage are summarized (i.e. reduced)





Examples?

Examples of Map Reduce

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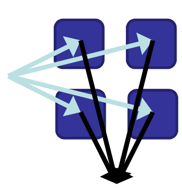
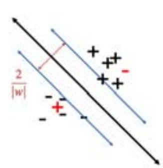
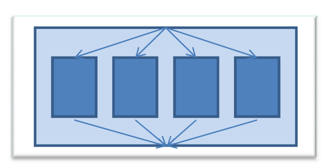
- General structure:
- Map a computation across distributed data sets
- Reduce the results to find the best/(worst), maxima/(minima)







Support-vector machines (ML)
• Map to evaluate distance from the frontier
• Reduce to find the greatest outlier from the frontier

Speech recognition
• Map HMM computation to evaluate word match
• Reduce to find the most-likely word sequences

Outline

- Architecting Parallel Software
- Structural Patterns
- Computational Patterns
  - Linear Algebra
  - Spectral Methods
  - Dynamic programming
- Examples
- Summary

Inventory of Key Computations

Apps / Dwarves	Embed	SPEC	DB	Games	ML	HPC	CAD	Health	Image	Speech	Music	Browser
Graph Algorithms												
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Backtrack / B&B												
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Dynamic Prog.												
Unstructured Grid												
Structured Grid												
Dense Matrix												
Sparse Matrix												
Spectral (FFT)												
Monte Carlo												
N-Body												

- We build arbitrarily complex computations out of these thirteen computational patterns

CP1: Linear Algebra

- **Vector Space**: A set closed under + has identity and inverse elements, scalar multiplication
- **Linear Map**: Operator **T** on vectors u,v, scalar α s.t. **T**(u + v) = **T**u + **T**v, and **T**(αv) = α**T**(v)
- **Matrix**: An m × n array of numbers representing a Linear map from R^n to R^m
- **Linear Equations**: Ax = b
- **Eigenvalues/vectors**: Ax = λx

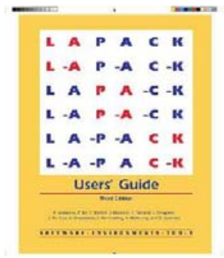
Basic Linear Algebra Subroutines (BLAS)

- Three "Levels", known as BLAS, characterized by intrinsic ratio of computation to memory movement

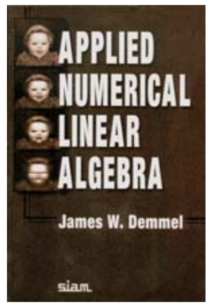
Level	Example	# mem refs	# flops	q
1	xAXPY: y = y+αx	3n	$2n^1$	2/3
2	xGEMV: y=y+Ax	n^2	$2n^2$	2
3	xGEMM: C=C+AB	$4n^2$	$2n^3$	n/2

Linear Algebra Resources

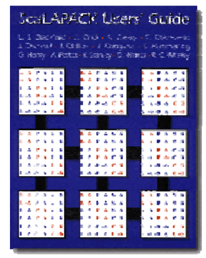
PARLAB



www.netlib.org/lapack



gams.nist.gov



www.netlib.org/scalapack

www.netlib.org/templates

www.cs.utk.edu/~dongarra/etemplates

CP2: Spectral Methods Pattern: MRI Reconstruction

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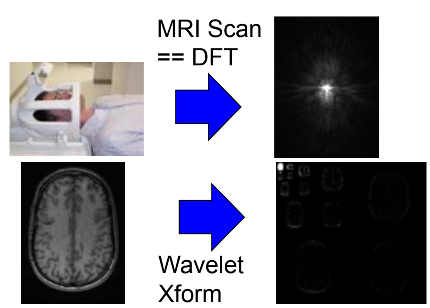
- "Spectral Methods" are a broad class of numerical algorithms for solving PDEs, but notions of Spectral Analysis (i.e. convenient changes of basis) are important in every application area
- In Magnetic Resonance Imaging (MRI), images are collected in "k-space" -- i.e. an MRI scan produces a Fourier Domain image
- Fourier and Wavelet representations are different Spectral analyses that expose different properties of images convenient for solving our problems



Spectral Methods Pattern: Fast Transforms

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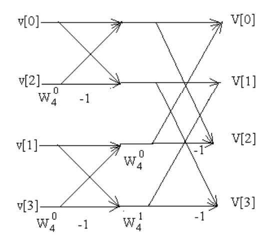
- Spectral Methods rely on represenions of data in "convenient" bases that produce working, computationally *feasible* algorithms
- Changing a basis is, in general, an O(N^2) matrix-vector multiplication. The matrices representing "convenient" bases factor into O(N log N) fast transforms!

$$u_k = \sum_{j=0}^{N-1} x_j \, \omega^{jk}$$

$$F = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & \omega & \omega^2 & \omega^3 \\ 1 & \omega^2 & \omega^4 & \omega^6 \\ 1 & \omega^3 & \omega^6 & \omega^9 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{bmatrix}$$

$$F_n x = \begin{bmatrix} I_{n/2} & D_{n/2} \\ I_{n/2} & -D_{n/2} \end{bmatrix} \begin{bmatrix} F_{n/2} x_{even} \\ F_{n/2} x_{odd} \end{bmatrix}$$



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Spectral Methods Pattern: Libraries

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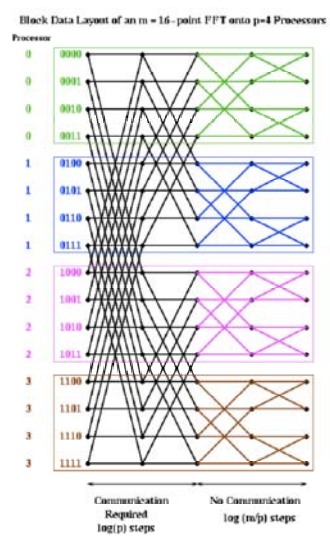
- Fast transform algorithms like the FFT are notoriously difficult to optimize:
- Luckily, implementations of the FFT exist for every platform. E.G:
  - FFTW and SPIRAL: Highly successful auto-tuners for FFT (and others) on PCs and workstations
  - CUFFT for Cuda on Nvidia GPUs



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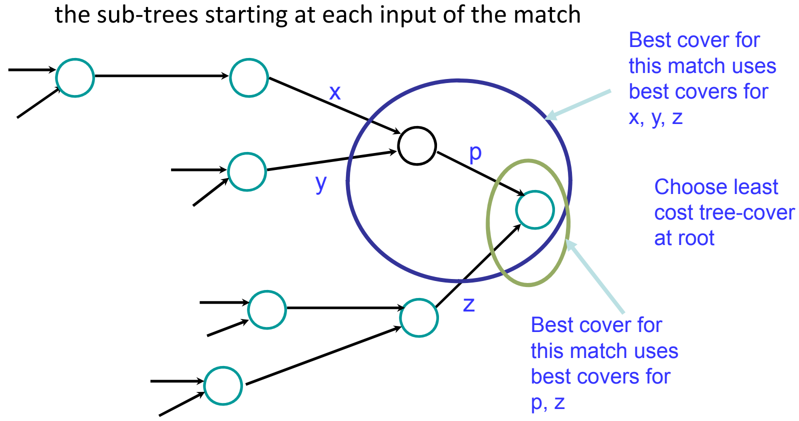
CP3: Dynamic Programming

- Class of problems for which the optimal solution can be built up from optimal solutions to sub-problems
- Principle of optimality: Optimal cover for a tree consists of a best match at the root of the tree plus the optimal cover for the sub-trees starting at each input of the match



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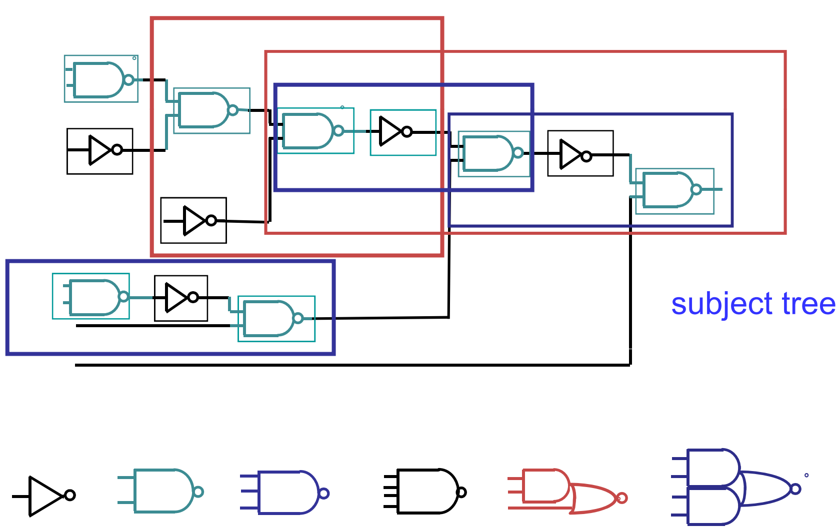
Mapping a circuits into a Cell Library



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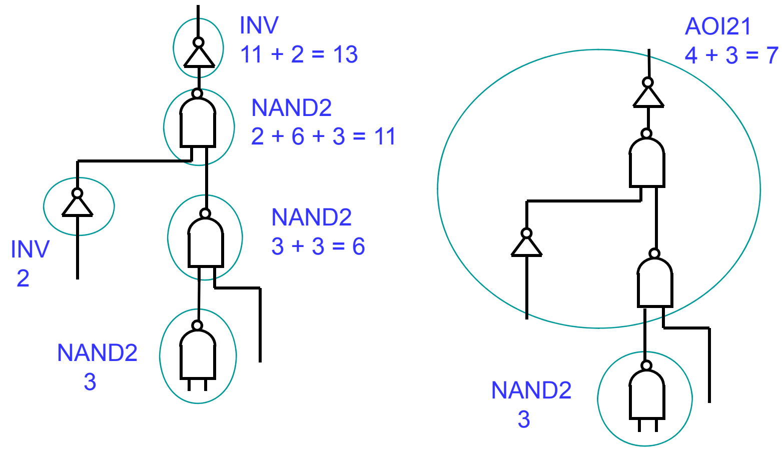
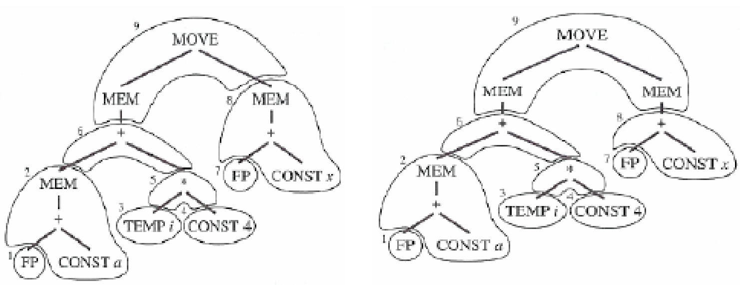
Example of Optimal Tree Covering



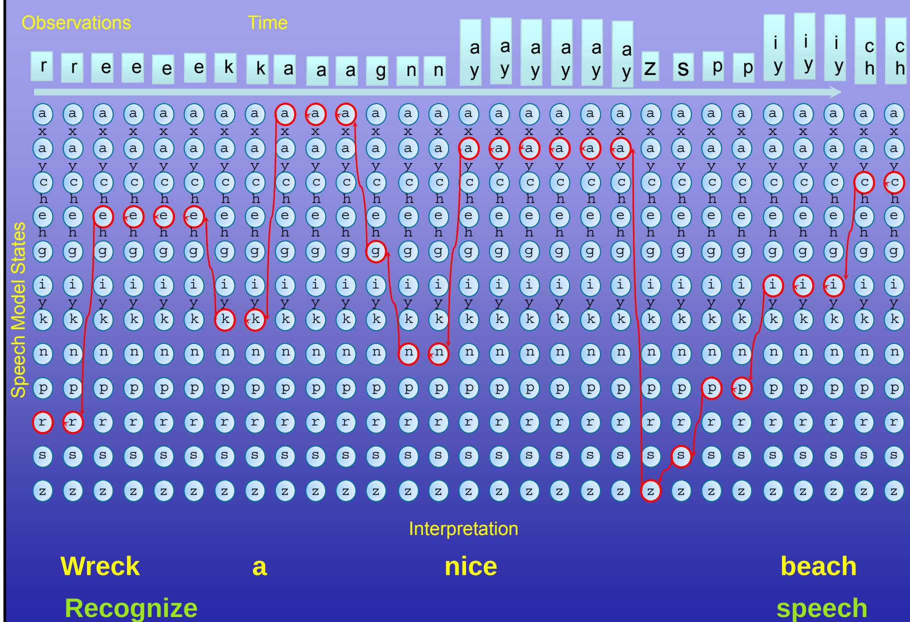
code generation in compilers



2	LOAD	$r_1 \leftarrow M[\mathbf{fp} + a]$
4	ADDI	$r_2 \leftarrow r_0 + 4$
5	MUL	$r_2 \leftarrow r_i \times r_2$
6	ADD	$r_1 \leftarrow r_1 + r_2$
8	LOAD	$r_2 \leftarrow M[\mathbf{fp} + x]$
9	STORE	$M[r_1 + 0] \leftarrow r_2$

2	LOAD	$r_1 \leftarrow M[\mathbf{fp} + a]$
4	ADDI	$r_2 \leftarrow r_0 + 4$
5	MUL	$r_2 \leftarrow r_i \times r_2$
6	ADD	$r_1 \leftarrow r_1 + r_2$
8	ADDI	$r_2 \leftarrow \mathbf{fp} + x$
9	MOVEM	$M[r_1] \leftarrow M[r_2]$

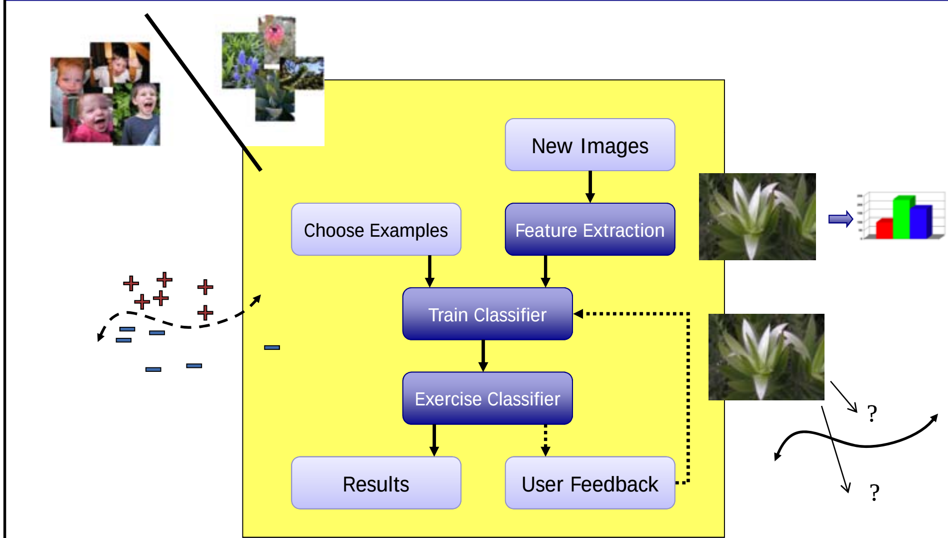
Speech Recognition



Outline

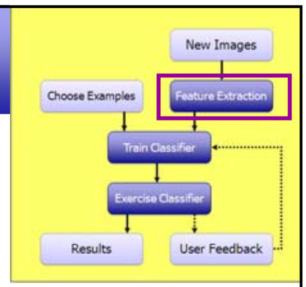
- Architecting Parallel Software
- Structural Patterns
- Computational Patterns
- Examples
  - Classification using Support Vector Machines
  - MRI
  - Speech Recognition
- Summary

Support Vector Machine Classifier

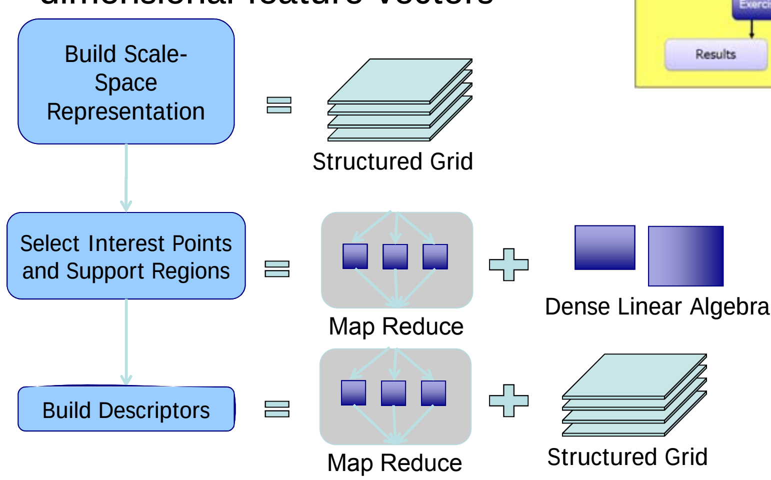


Catanzaro, Sundaram, Keutzer, “Fast SVM Training and Classification on Graphics Processors”, ICML 2008

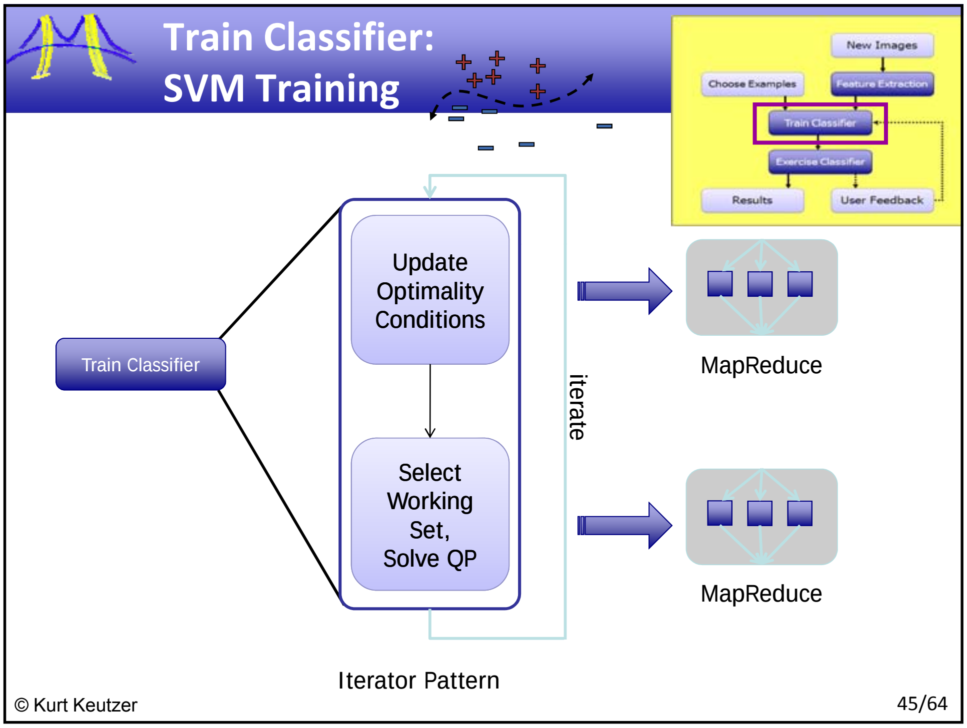
Feature Extraction



- Image is reduced to a set of low-dimensional feature vectors



"Image Feature Extraction for Mobile Processors", Mark Murphy, Hong Wang, Kurt Keutzer IISWC '09


Train Classifier:
SVM Training
New Images
Choose Examples
Feature Extraction
Train Classifier
Exercise Classifier
Results
User Feedback
Train Classifier
Update Optimality Conditions
Select Working Set, Solve QP
iterate
MapReduce
MapReduce
Iterator Pattern
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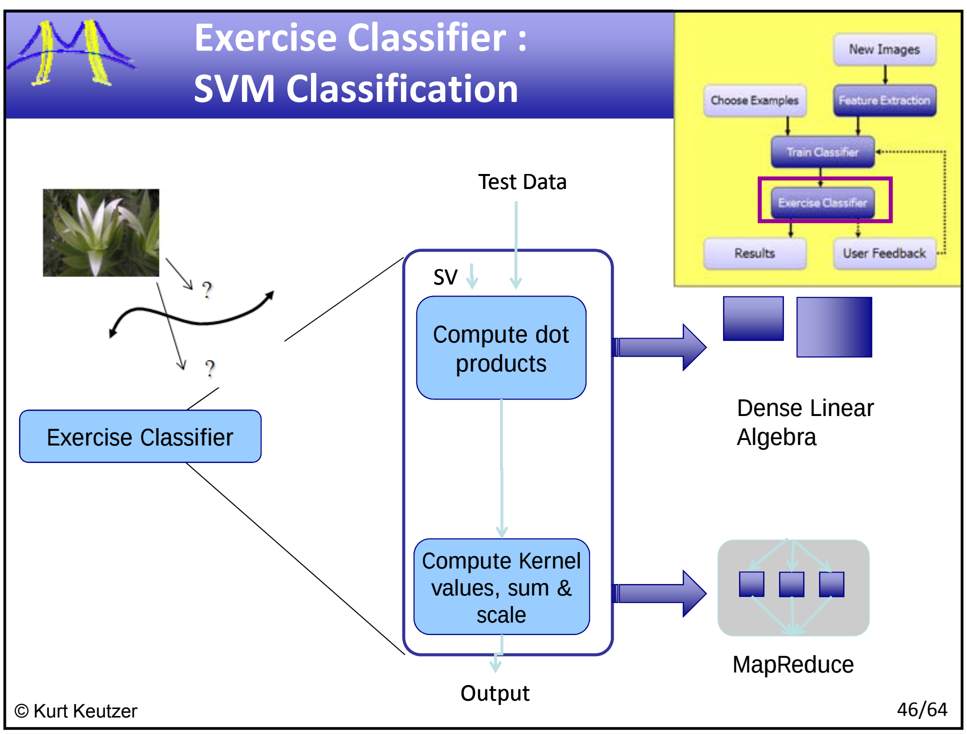
Exercise Classifier :
SVM Classification
New Images
Choose Examples
Feature Extraction
Train Classifier
Exercise Classifier
Results
User Feedback
Test Data
SV
Compute dot products
Compute Kernel values, sum & scale
Output
Exercise Classifier
Dense Linear Algebra
MapReduce
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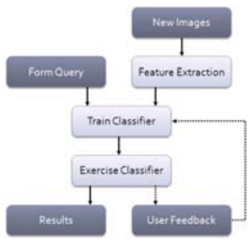
Support-Vector Machine Mini-Framework



- Support-Vector Machine Framework used to achieve:
  - 9-35x speedup for training
  - 81-138x for classification
- 1100 downloads since release

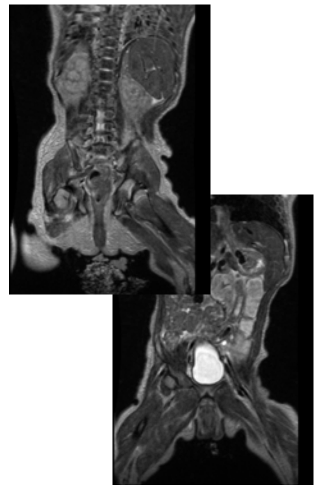
Fast support vector machine training and classification , Catanzaro, Sundaram, Keutzer, International Conference on Machine Learning 2008

Outline

- Architecting Parallel Software
- Structural Patterns
- Computational Patterns
- Examples
  - CBIR
  - MRI
  - Speech Recognition
- Summary

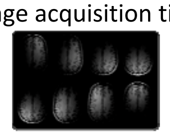
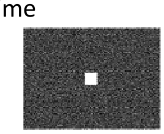
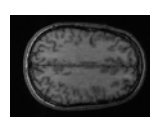
Compelling Application: Fast, Robust Pediatric MRI

- Pediatric MRI is difficult:
  - Children cannot sit still, breathhold
  - Low tolerance for long exams
  - Anesthesia is costly and risky
- Like to accelerate MRI acquisition
  - Advanced MRI techniques exist, but require data- and compute- intense algorithms for image reconstruction
- Reconstruction must be fast, or time saved in accelerated acquisition is lost in computing reconstruction
  - Slow reconstruction times are a non-starter for clinical use



Domain Experts and State-of-the-Art Algorithms

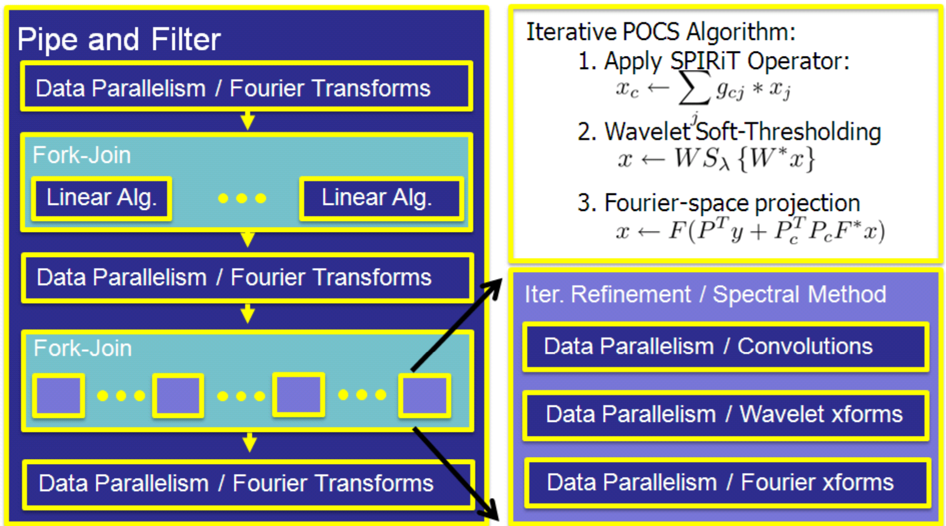
- Collaboration with MRI Researchers:
  - Miki Lustig, Ph.D., Berkeley EECS
  - Marc Alley, Ph.D., Stanford EE
  - Shreyas Vasanawala, M.D./Ph.D., Stanford Radiology
- Advanced MRI: Parallel Imaging and Compressed Sensing to dramatically reduce MRI image acquisition time

- Computational IOU: Must solve constrained L1 minimization

$$\begin{aligned} \text{minimize} \quad & ||Wx||_1 \\ \text{s.t} \quad & \mathbf{F}_\Omega x = y, \\ & ||\mathbf{G}x - x||_2 < \varepsilon \end{aligned}$$

SW architecture of image reconstruction



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Game-Changing Speedup

- 100X faster reconstruction
- Higher-quality, faster MRI
- This image: 8 month-old patient with cancerous mass in liver
  - 256 x 84 x 154 x 8 data size
  - Serial Recon: 1 hour
  - Parallel Recon: 1 minute
- Fast enough for clinical use
  - Software currently deployed at Lucile Packard Children's Hospital for clinical study of the reconstruction technique

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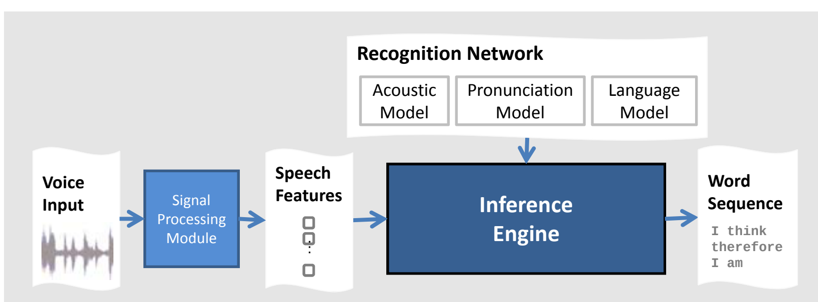
Large Vocabulary Continuous Speech Recognition



- Inference engine based system
  - Used in Sphinx (CMU, USA), HTK (Cambridge, UK), and Julius (CSRC, Japan) [10,15,9]
- Modular and flexible setup
  - Shown to be effective for Arabic, English, Japanese, and Mandarin

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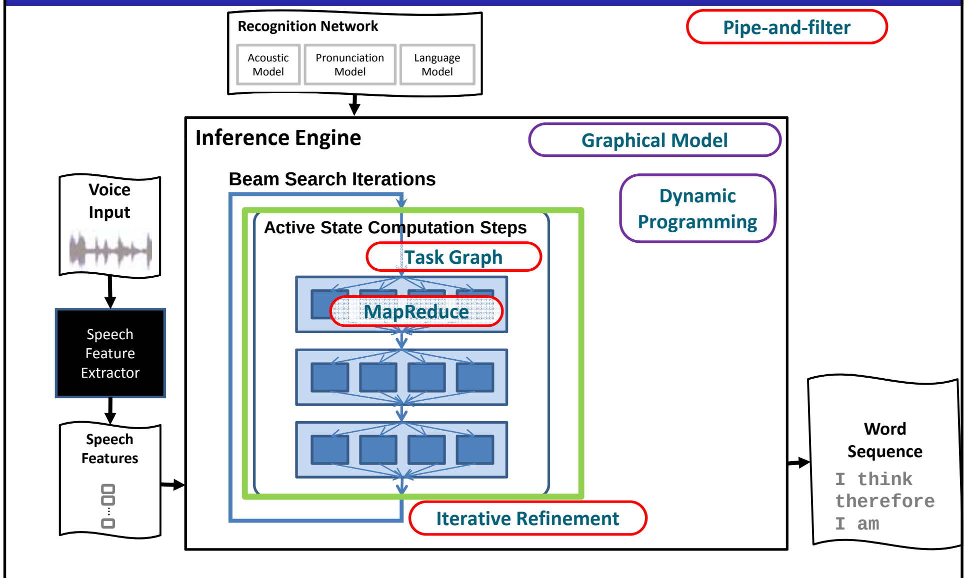
LVCSR Software Architecture

PALLAS



Key computation: HMM Inference Algorithm

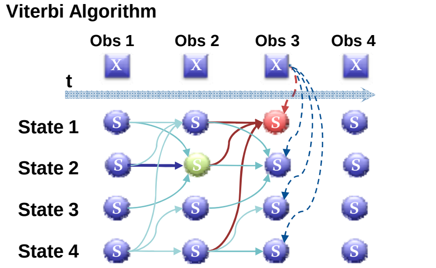
PALLAS

An instance of: **Graphical Models** | Implemented with: **Dynamic Programming**

- Finds the most-likely sequence of states that produced the observation

$$m[t][s_t] = \max_{s_{t-1}} m[t-1][s_{t-1}] \cdot P(s_t|s_{t-1}) \cdot P(x_t|s_t)$$

Viterbi Algorithm



Legends:

S A State X An Observation

$P(x_t|s_t)$ $m[t-1][s_{t-1}]$

$P(s_t|s_{t-1})$ $m[t][s_t]$

Markov Condition:

$$m[t][s_t] \doteq \max_{s_0,\ldots,s_{t-1}} P(x_0,\ldots,x_t,s_0,\ldots,s_{t-1},s_t)$$

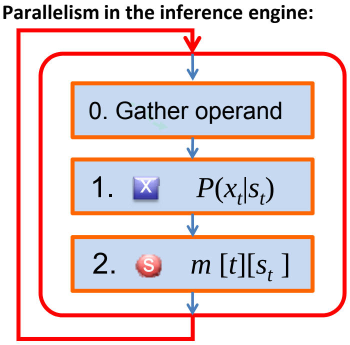
J. Chong, Y. Yi, A. Faria, N.R. Satish and K. Keutzer, "**Data-Parallel Large Vocabulary Continuous Speech Recognition on Graphics Processors**", Emerging Applications and Manycore Arch. 2008, pp. 23-35, June 2008

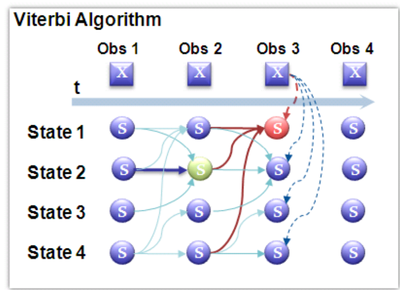
Inference Engine in LVCSR

PALLAS

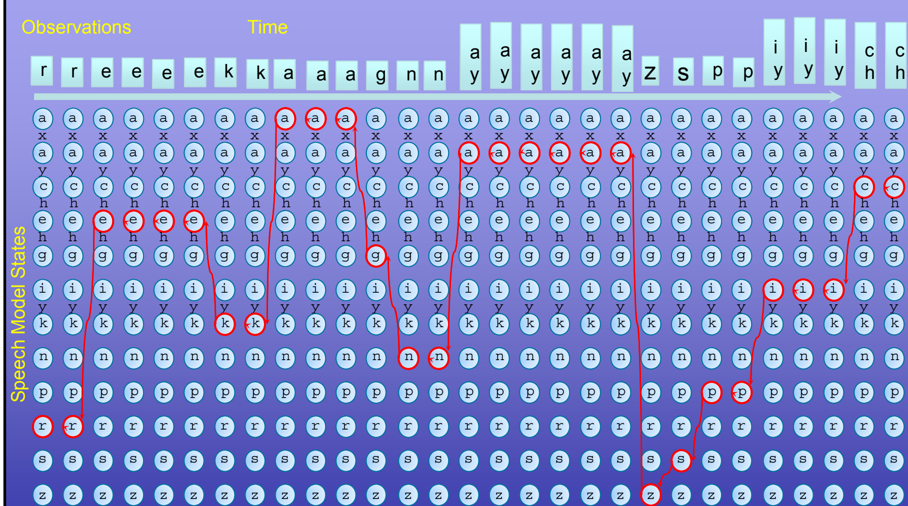
- Three steps of inference
    0. Gather operands from irregular data structure to runtime buffer
    1. Perform observation probability computation
    2. Perform graph traversal computation

Parallelism in the inference engine:





Speech Recognition with HMM



Interpretation

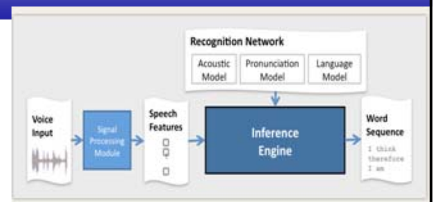
Wreck **a** **nice** **beach**

Recognize **speech**

Speech Recognition Results

PALLAS

- Input: Speech audio waveform
- Output: Recognized word sequences



- Achieved 11x speedup over sequential version
- Allows 3.5x faster than real time recognition

- Our technique is being deployed in a hotline call-center data analytics company
- Used to search content, track service quality and provide early detection of service issues

Scalable HMM based Inference Engine in Large Vocabulary Continuous Speech Recognition, Kisun You, Jike Chong, Youngmin Yi, Ekaterina Gonina, Christopher Hughes, Wonyong Sung and Kurt Keutzer, IEEE Signal Processing Magazine, March 2010

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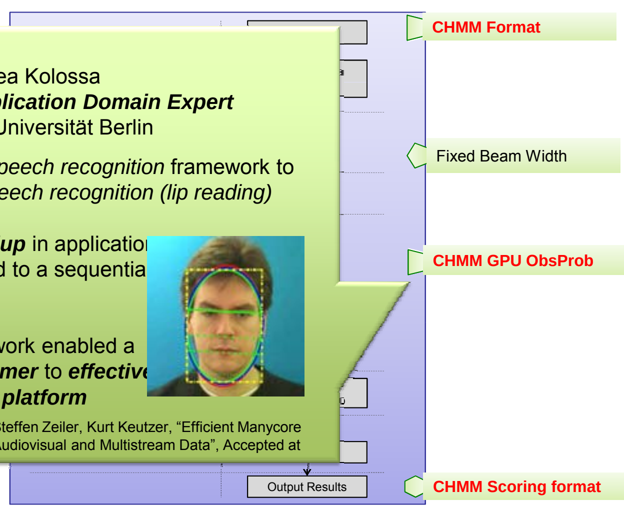
Multi-media Speech Recognition

PALLAS



Prof. Dorothea Kolossa
Speech Application Domain Expert
Technische Universität Berlin

Extended *audio-only speech recognition* framework to enable *audio-visual speech recognition (lip reading)*

Achieved a ***20x speedup*** in application performance compared to a sequential version in C++

The application framework enabled a ***Matlab/Java programmer*** to ***effectively utilize highly parallel platform***

Dorothea Kolossa, Jike Chong, Steffen Zeiler, Kurt Keutzer, "Efficient Manycore CHMM Speech Recognition for Audiovisual and Multistream Data", Accepted at Interspeech 2010.

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Other Interesting Results

PALLAS

- Patterns have helped the PALLAS research group publish papers in a diverse group of leading Computer Science conferences in the last few years:
  - Interspeech 2009, Interspeech 2010 (2)
  - IEEE Signal Processing Magazine 2009
  - European Conference on Computer Vision 2010
  - International Conference on Computer Vision 2009
  - Workshop on High Performance Computing in Finance at Super Computing 2009
  - Joint Annual Meeting of the International Society for Magnetic Resonance in Medicine*, ISMRM 2010*
  - International Conference on Machine Learning 2008
- What's the point?
  - Computational patterns give a new powerful viewpoint to efficiency programmers:
  - Enable us to disentangle the big fuzzy ball of yarn of computation
    - add 20 IQ points to our problem solving (as per Alan Kay)
  - Our Pattern language helps you to write good parallel code

Summary

PALLAS

- The key to productive and efficient parallel programming is creating a good software architecture – a hierarchical composition of:
- Structural patterns: enforce modularity and expose invariants
  - I showed you three –seven more will be all you need
- Computational patterns: identify key computations to be parallelized
  - I showed you three –ten more will be all you need
- Orchestration of computational and structural patterns creates architectures which greatly facilitates the development of parallel programs:
  - I showed you three – there are *many* more

Patterns: http://parlab.eecs.berkeley.edu/wiki/patterns/patterns

PALLAS: http://parlab.eecs.berkeley.edu/research/pallas

CS194: Engineering Parallel Software: Fall 2010

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