Pricing Python Parallelism

A Dynamic Language Cost Model for Heterogeneous Platforms

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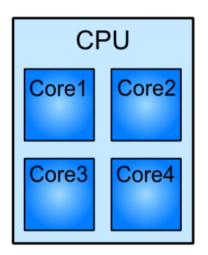
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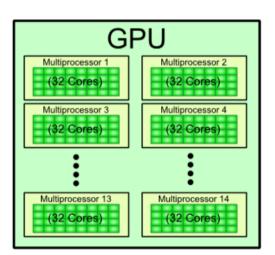
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School of Computing Science

Heterogeneous architectures





ALPyNA

ALPyNA Novelties

- Staged parallelisation Hybrid Static/Dynamic approach
- Preserving static analysis to aid runtime discovery of parallelism
- Runtime introspection of types and dependences
- Automatic loop parallelisation in a dynamic language

Novelties of ALPyNA Cost Model (ACM)

- Analytical cost model.
- Parametric should account for differing hardware characteristics.
- Dynamic sequential/parallel code structure can change.
- Light weight JIT environment does not tolerate prediction latency.



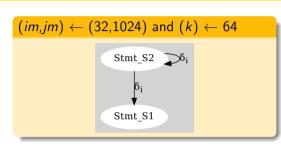
Runtime dependence analysis

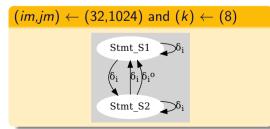
```
import numpy as np

def In_func(arg_a,k,limits):
    im, jm = limits
    for i in range(0,im,1):
        for j in range(0,jm,1):
        # Statement - S1
        arg_a[i+k,j] = arg_a[i,j] + 4
        # Statement - S2
        arg_a[i+16,j] = arg_a[i,j]
```

Runtime dependence analysis

```
import numpy as np
def In_func(arg_a,k,limits) :
im, jm = limits
 for i in range(0,im,1):
  for j in range(0,jm,1):
     # Statement - S1
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     # Statement - S2
     arg_a[i+16,i] = arg_a[i,i]
```





ACM Interpreter and CPU modelling

- Absolute cost model: predicts runtime
- Relative cost model: compares runtimes

Interpreter loop nest

$$C_{\mathrm{int}}(s) = I_{\mathrm{int}}(s) \prod_{f \in \mathcal{D}(s)} \mathcal{L}(f)$$

$$\mathcal{T}_{\mathrm{int}}(f) = \sum_{s \in \mathcal{E}(f)} \mathcal{C}_{\mathrm{int}}(s)$$

CPU loop nest

$$C_{ ext{cpu}}(s) = I_{ ext{cpu}}(s) \prod_{f \in \mathcal{D}(s)} \mathcal{L}(f)$$

$$\mathcal{T}_{ ext{cpu}}(f) = \sum_{s \in \mathcal{E}(f)} \mathcal{C}_{ ext{cpu}}(s)$$



GPU - SIMT Architecture

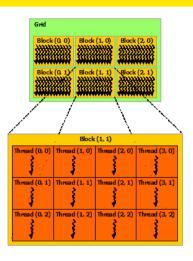


Figure: source:NVIDIA

Modelling GPU execution

Loop identification and splitting

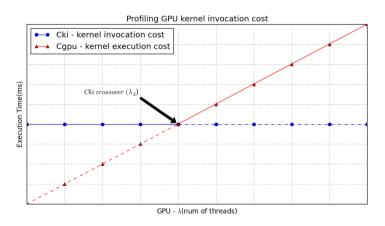
- loops executed sequentially on CPU: $\mathcal{D}_{seq}(s)$
- loops executed on GPU: $\mathcal{D}_{par}(s)$
 - loops executed with parallel threads: $\mathcal{D}_{gpu}(s)$
 - loops executed sequentially within kernels: $\mathcal{D}_{\overline{gpu}}(s)$

Cost of parallel execution on GPU

$$\lambda_{\mathsf{exec}}(s) = \left\lceil rac{g}{u}
ight
ceil imes rac{1}{g.v.w} imes \prod_{f \in \mathcal{D}_{\mathsf{gpu}}(s)} \mathcal{L}(f) imes \prod_{f \in \mathcal{D}_{\overline{\mathsf{gpu}}}(s)} \mathcal{L}(f)$$

$$g = \prod_{f \in \mathcal{D}_{gou}(s)} \mathcal{G}(\mathcal{L}(f))$$

Accounting for GPU invocation



Smaller GPU workloads are executed faster on the GPU than the interpreter can dispatch a new kernel: the GPU is starved for work.

Calibration to calculate relative cost

Ideal compiled CPU execution relative to VM

$$\mu = \frac{I_{\text{int}}(s)}{I_{cpu}(s)} \tag{1}$$

Relative cost of GPU execution incorporates terms to account for CPU and (shared) GPU caches

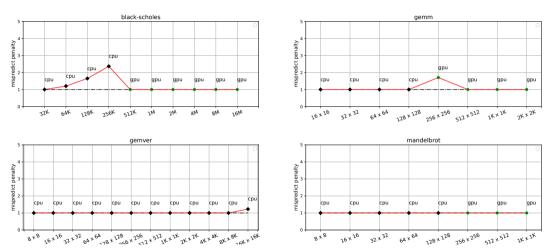
$$\frac{I_{cpu}(s)}{I_{gpu}(s)} = \psi \approx \frac{f_{gpu} \times (LC_{gpu}/\sigma)}{f_{cpu} \times LC_{cpu}}$$
(2)

 σ – cache sharing factor for GPU. CPU is single threaded.

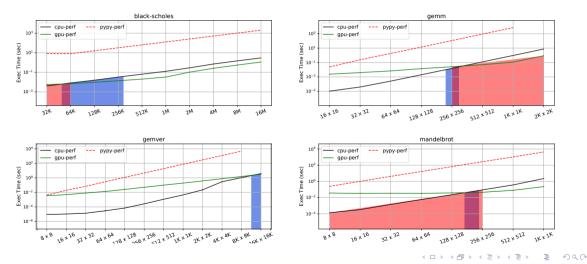
Derived GPU per core performance

$$\frac{I_{\text{int}}(s)}{I_{\text{gpu}}(s)} \approx \mu \times \psi \tag{3}$$

Experimental Results – prediction performance



Experimental Results - misprediction range



Conclusion

- A lightweight analytical cost model to select the faster compute device for a loop nest in a heterogeneous architecture.
- 2 Adapts to runtime dependence analysis and code generation.
- Minimal install time profiling required
- Overall 13.6% mean slowdown due to mispredictions.
- Overall 14.3% mean misprediction across iteration domain sizes

Conclusion

Publications

- DLS-20 doi:10.1145/3426422.3426979
- DLS-19 doi:10.1145/3359619.3359743
- ARRAY-19: doi:10.1145/3315454.3329956
- Source: https://bitbucket.org/djichthys/alpyna/src/master

