Introduction to Query Engines

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- *power the business world*

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- different hardware/environments

Sometimes other criteria (e.g., robustness) are more important

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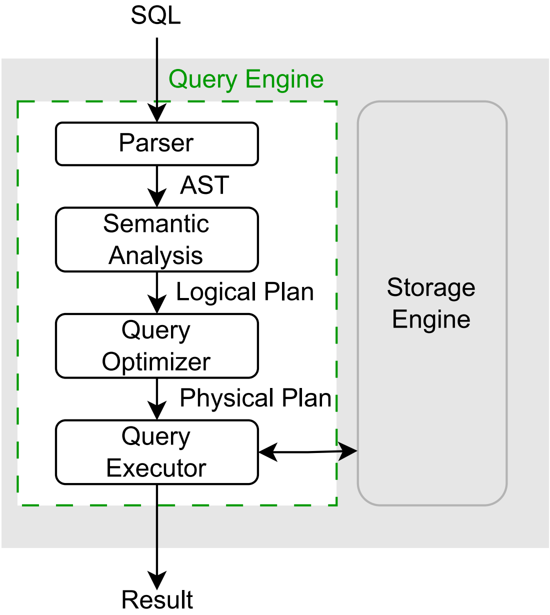
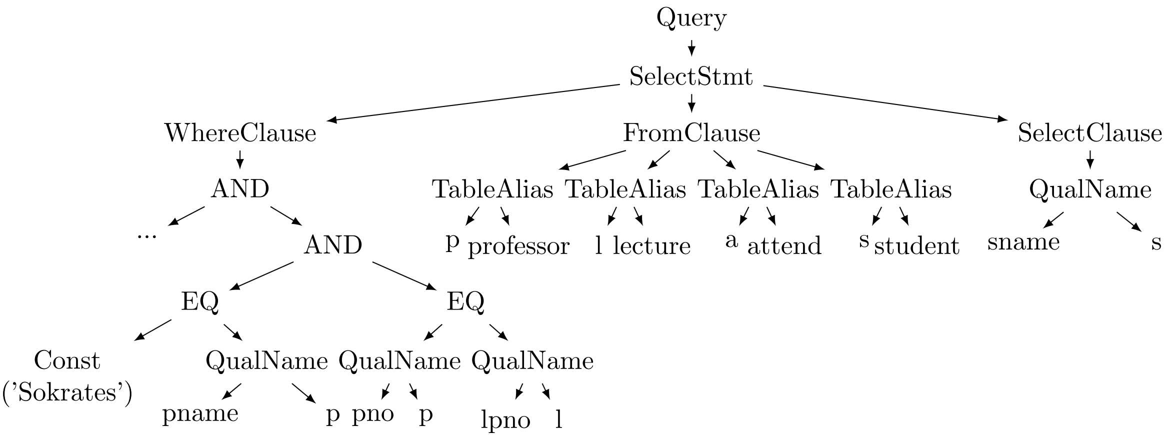


Query Engine: SQL Query

```sql
select s.sname
from student s, attend a, lecture l, professor p
where s.sno = a.asno and a.alno = l.lno and
      l.lpno = p.pno and p.pname ='Sokrates'
```

Query Engine: Parser & Semantic Analysis

- Parser creates abstract syntax tree (AST)



- Semantic Analysis: resolve references, type inference, eliminate syntactic sugar

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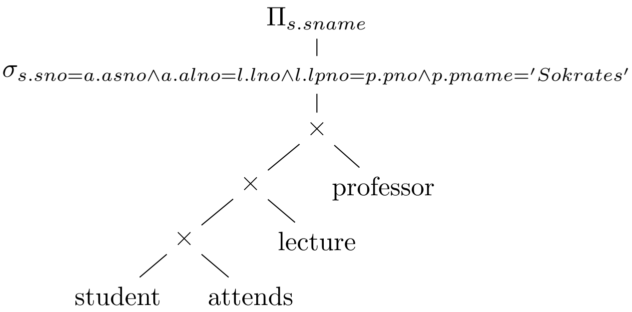

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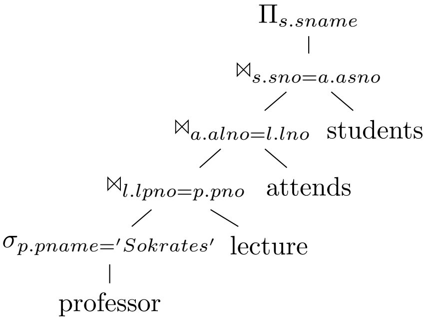

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  - Hash-based: use hash-tables for implementing for example *hash*-joins and *hash*-aggregations
  - Sorting-based: sorts data and then exploits this for *sortmerge*-joins or *sort-based* aggregations

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```
class Iterator:
    def open()
    def next()

class Output(Iterator):
  def next():
      while True:
          row = child.next()
          if row is None: break
          print(row)

class TableScan(Iterator):
      i = 0
  def next():
      if i >= len(table): return None
      row = table[i]
      i += 1
      return row

class Selection(Iterator):
  def next():
      while True:
          row = child.next()
          if row is None: return None
          if pred(row): return row
```

```
class HashJoin(Iterator):

  def open():
    ht = {}
    # build hashtable with left size
    while True:
      l = left.next()
      if l is None: break
      ht.insert(l)
    q = queue()

  def next():
      # we still have tuples left
      if q: return q.pop()
      # we need to get a new tuple
      while True:
          r = right.next()
          if r is None: return None
          # compute matches for current
          for m in ht.lookup(r):
            q.push(m+r)
          # return first match
          if q: return q.pop()
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  - Hyper (push, compile, tuple-at-a-time)
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- A lot more benchmarks exist with a different focus (e.g., JOB, SSB, clickbench)

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LingoDB

- started 2021
- open source