进度

1. 数据

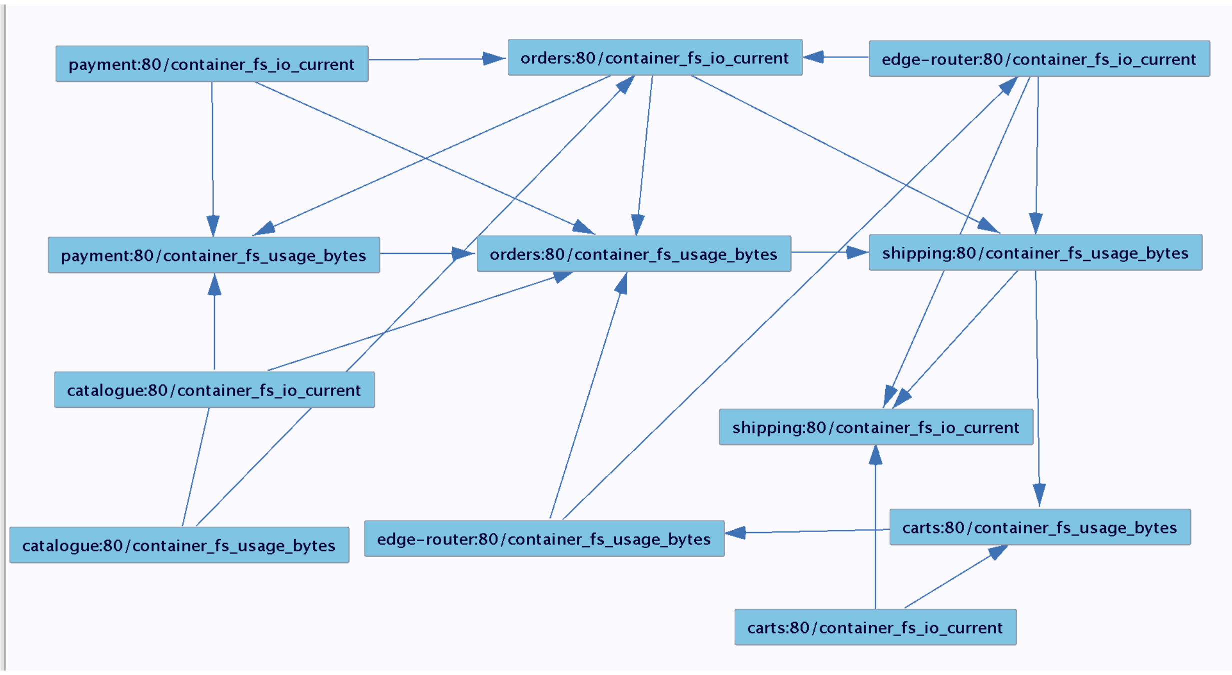
1.1 数据集概况

- 与殷博对接，有了初步的数据集：result.csv
- columns：212
- 存在的问题：
  - 数据量太大，无法直接搜索
  - 部分列值全为0
  - 存在大量null，Tetrad无法处理null值，与殷博讨论解决策略

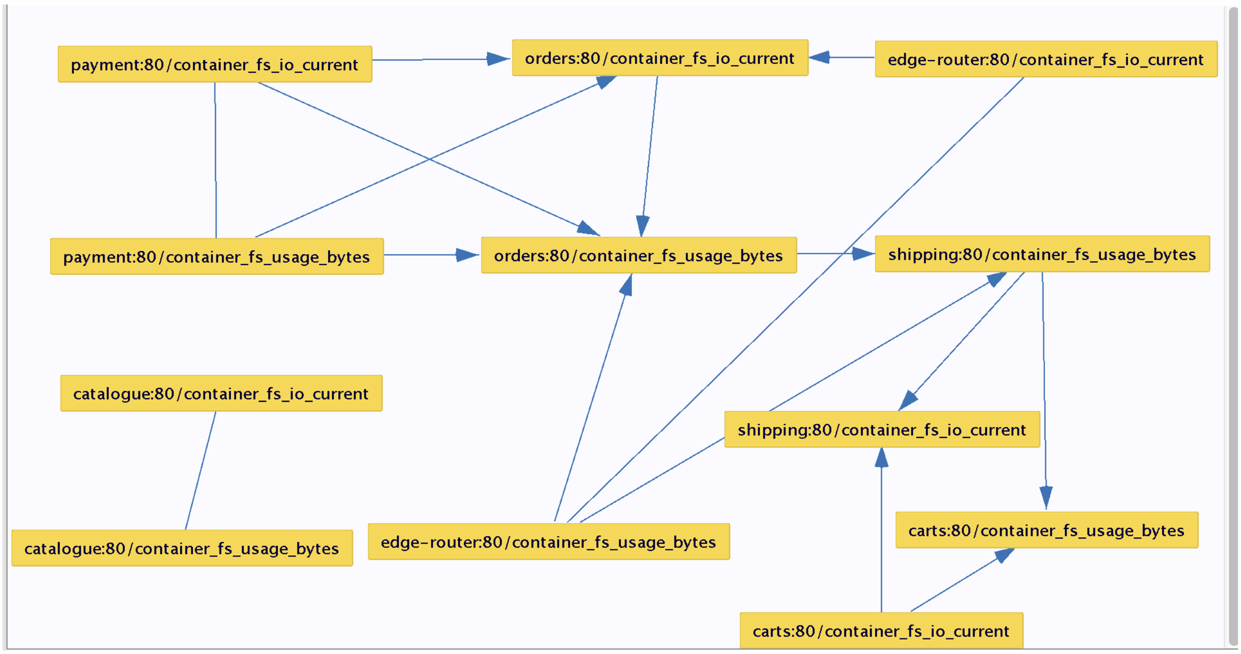
1.2 数据执行情况

- 预处理：
  - service_data.csv
  - 只抽取了服务层性能数据, 14列，其中2列数据均为0，舍去，留12列
  - null暂时填0代替
  - 总体来看，0与null占相当大一部分
- 执行结果

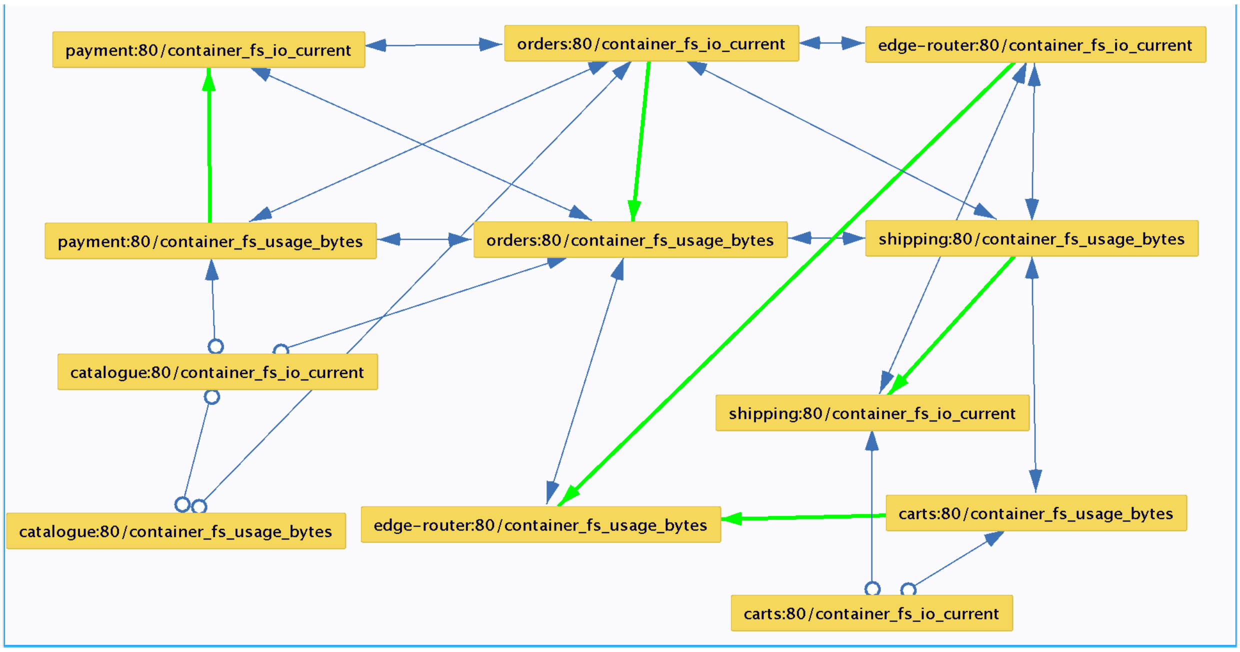
PC + Correlation T Test or Fisher Z Test or Mutinomial Logestic RW Test



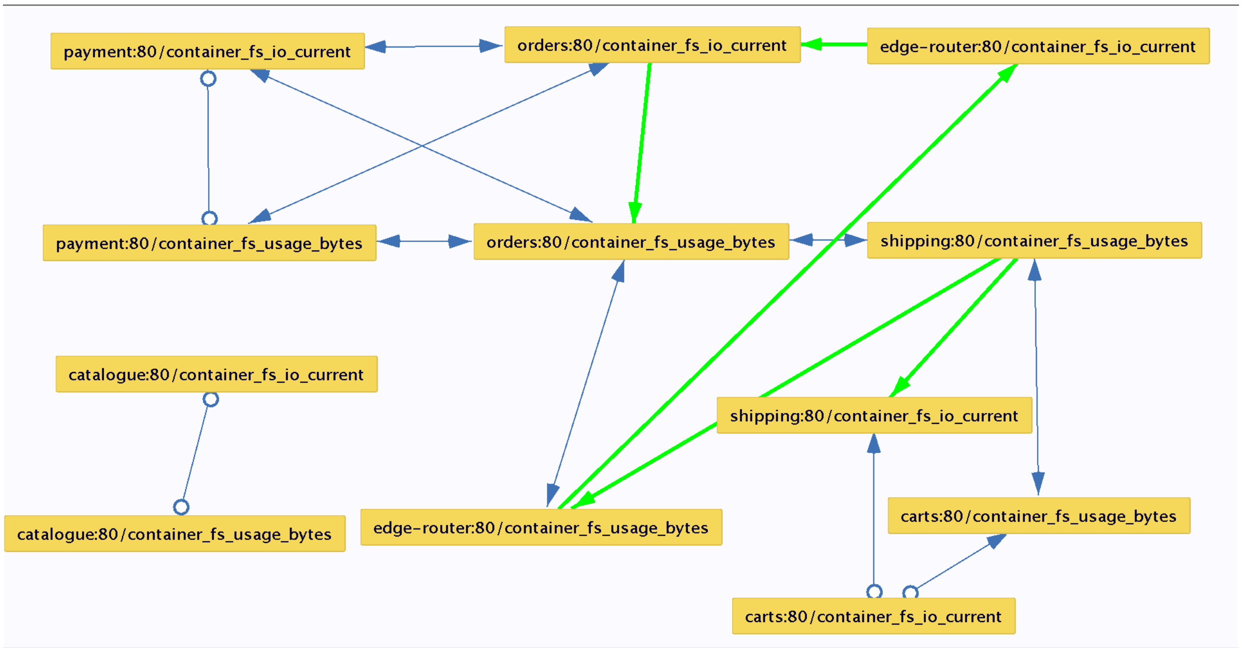
PC + SEM BIC Test



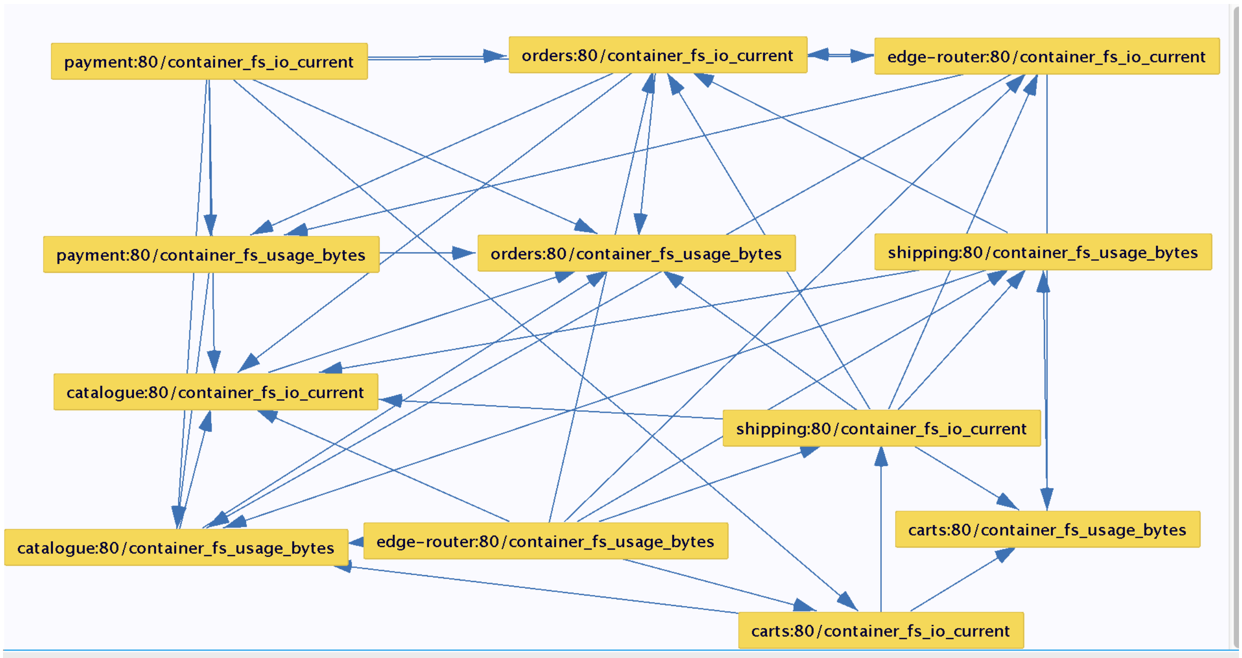
FCI + Fisher Z Test or Correlation T Test or Mutinomial Logestic RW Test



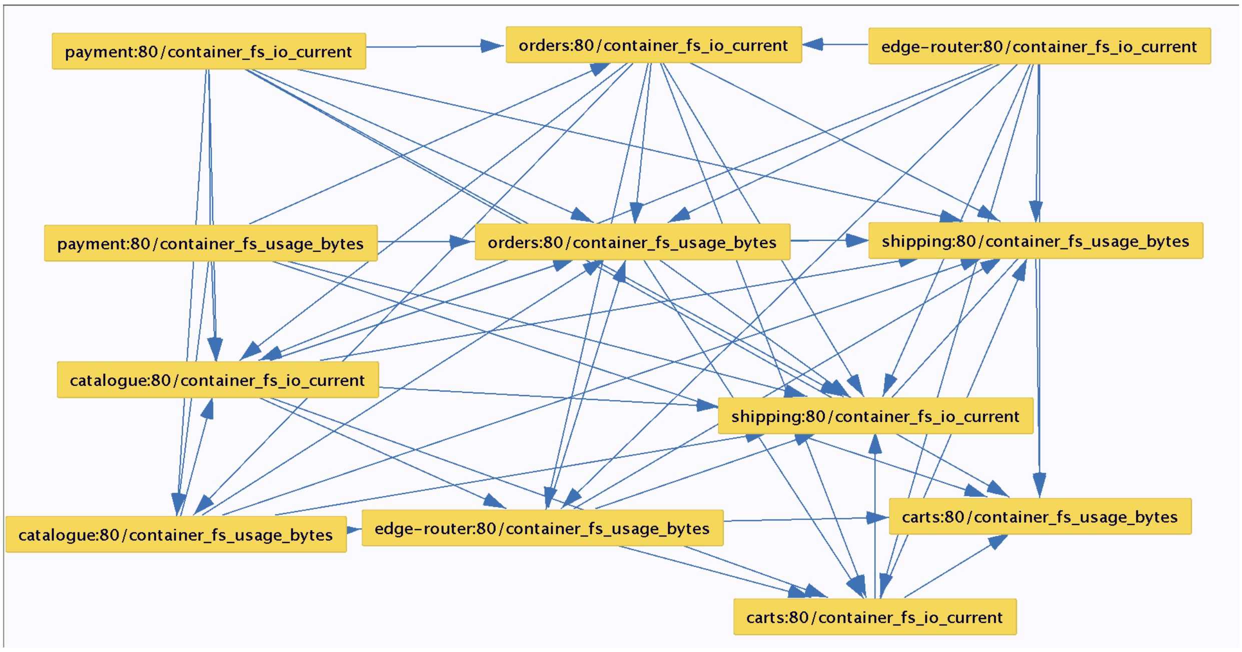
FCI + SEM BIC Test



FGES + SEM BIC



FGES + Fisher Z Score



FCI 与PC在使用相同的test方法情况下，所得结果基本相同。

Mutinomial Logestic RW Test执行速度较慢，

其他Conditional Correlation Test 等执行速度过慢，无法得到结果

2.算法

2.1 源码研究

影响图构建核心3步骤：

1. 构建无向完全图
2. 独立性检验并删除条件独立的边
3. 边的定向化

其中，步骤1可以忽略，步骤三有ruler1-4，在源码中有规范的实现：

```
    # For all the combination of nodes i and j, apply the following
    # rules.
    for (i, j) in combinations(node_ids, 2):
        # Rule 1: Orient i-j into i->j whenever there is an arrow k->i
        # such that k and j are nonadjacent.
        #
        # Check if i-j.
        if _has_both_edges(dag, i, j):
            # Look all the predecessors of i.
            for k in dag.predecessors(i):
                # Skip if there is an arrow i->k.
                if dag.has_edge(i, k):
```

```
                continue
            # Skip if k and j are adjacent.
            if _has_any_edge(dag, k, j):
                continue
            # Make i-j into i->j
            _logger.debug('R1: remove edge (%s, %s)' % (j, i))
            dag.remove_edge(j, i)
            break
        pass

    # Rule 2: Orient i-j into i->j whenever there is a chain
    # i->k->j.
    #
    # Check if i-j.
    if _has_both_edges(dag, i, j):
        # Find nodes k where k is i->k.
        succs_i = set()
        for k in dag.successors(i):
            if not dag.has_edge(k, i):
                succs_i.add(k)
                pass
            pass
        # Find nodes j where j is k->j.
        preds_j = set()
        for k in dag.predecessors(j):
            if not dag.has_edge(j, k):
                preds_j.add(k)
                pass
            pass
        # Check if there is any node k where i->k->j.
        if len(succs_i & preds_j) > 0:
            # Make i-j into i->j
            _logger.debug('R2: remove edge (%s, %s)' % (j, i))
            dag.remove_edge(j, i)
            break
        pass

    # Rule 3: Orient i-j into i->j whenever there are two chains
    # i-k->j and i-l->j such that k and l are nonadjacent.
    #
    # Check if i-j.
    if _has_both_edges(dag, i, j):
        # Find nodes k where i-k.
        adj_i = set()
        for k in dag.successors(i):
            if dag.has_edge(k, i):
                adj_i.add(k)
                pass
            pass
```

```
        # For all the pairs of nodes in adj_i,
        for (k, l) in combinations(adj_i, 2):
            # Skip if k and l are adjacent.
            if _has_any_edge(dag, k, l):
                continue
            # Skip if not k->j.
            if dag.has_edge(j, k) or (not dag.has_edge(k, j)):
                continue
            # Skip if not l->j.
            if dag.has_edge(j, l) or (not dag.has_edge(l, j)):
                continue
            # Make i-j into i->j.
            _logger.debug('R3: remove edge (%s, %s)' % (j, i))
            dag.remove_edge(j, i)
            break
        pass

    # Rule 4: Orient i-j into i->j whenever there are two chains
    # i-k->l and k->l->j such that k and j are nonadjacent.
    #
    # However, this rule is not necessary when the PC-algorithm
    # is used to estimate a DAG.
```

这部分完全根据图的结构特点进行定向化，不涉及矩阵数据。

独立性检验部分存在问题：

- Tetrad以及之前CloudRanger声称其算法实现基于《Causation, Prediction, and Search》，该书作者即为PC算法提出者。

A.) Form the complete undirected graph C on the vertex set **V**.
B.)
$n = 0$.
repeat
repeat
select an ordered pair of variables X and Y that are adjacent in C such that **Adjacencies**$(C,X)\backslash\{Y\}$ has cardinality greater than or equal to n, and a subset **S** of **Adjacencies**$(C,X)\backslash\{Y\}$ of cardinality n, and if X and Y are d-separated given **S** delete edge X - Y from C and record **S** in **Sepset**(X,Y) and **Sepset**(Y,X);

书中却是明确说到用D分离进行条件独立检验，不过没有给出检验细节过程。

尝试写D分离过程，发现如下问题：

- D分离的运用对象是有向图DAG，而我们目的是从无向完全图，求得有向图，过程正好相反
- D分离过程需要概率分布函数，我们的数据仅有一个监控数据的矩阵。

基于上述原因，D分离似乎不能用到这里，进行条件独立判断

Python代码中用了G-square进行独立检验，但是导入除示例数据外的数据均报错。

源码中表示其算法参考文献：《Estimating High-Dimensional Directed Acyclic Graphs with the PC-Algorithm》

察阅该文献，发现其给的例子并没真正用D分离，而是假设变量呈现

D-separation 算法又问题：

用于有向图（DAG）

文献：Estimating High-Dimensional Directed Acyclic Graphs with the PC-Algorithm

中假设了变量正态分布的条件

For finite samples, we need to estimate conditional independencies. We limit ourselves to the Gaussian case, where all nodes correspond to random variables with a multivariate normal distribution. Furthermore, we assume faithful models, which means that the conditional independence relations correspond to d-separations (and so can be read off the graph) and vice versa; see Section 2.1.

并且利用 partial correlations 求解概率分布

We can thus estimate partial correlations to obtain estimates of conditional independencies. The sample partial correlation $\hat{\rho}_{i,j|\mathbf{k}}$ can be calculated via regression, inversion of parts of the covariance matrix or recursively by using the following identity: for some $h \in \mathbf{k}$,

$$\rho_{i,j|\mathbf{k}} = \frac{\rho_{i,j|\mathbf{k}\setminus h} - \rho_{i,h|\mathbf{k}\setminus h}\rho_{j,h|\mathbf{k}\setminus h}}{\sqrt{(1-\rho^2_{i,h|\mathbf{k}\setminus h})(1-\rho^2_{j,h|\mathbf{k}\setminus h})}}.$$

2.2 代码分离

- 和殷博沟通解决Tetrad lib库中search算法的抽取工作

2.3 其他策略

改团队提供了其他工具： https://github.com/bd2kccd

包括Python借口，web应用，以及API接口，JAVA CMD

这些工具实质上都是调用Java包，只是外层封装不同。

3. 问题明确

- 算法选择
- 代码需要到什么程度，用API接口可行性