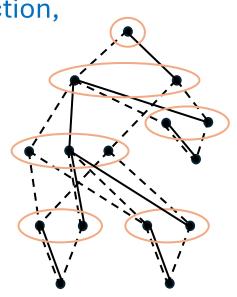
# **Nonserial Decision Diagrams**

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> ICS Conference March 2025

### Why Nonserial DDs?

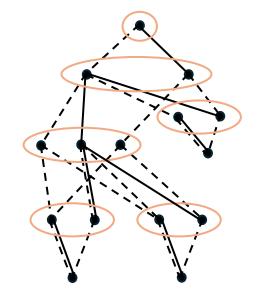
- They exploit structure of problem instances whose variables **partially decouple**.
- They combine **nonserial dynamic programming** ideas with **DD solution technology** reduction, relaxation, restriction, flow models, etc.
- They can be **dramatically smaller** than serial DDs.
- Reduction in **compilation time** is **even greater**.



### Why Nonserial DDs?

When exact DDs are **smaller**....

- **Relaxed DDs** of a given size provide **tighter bounds**.
- **Restricted DDs** of a given size are more likely to yield **feasible solutions**.
- Flow models are more likely to be tractable.

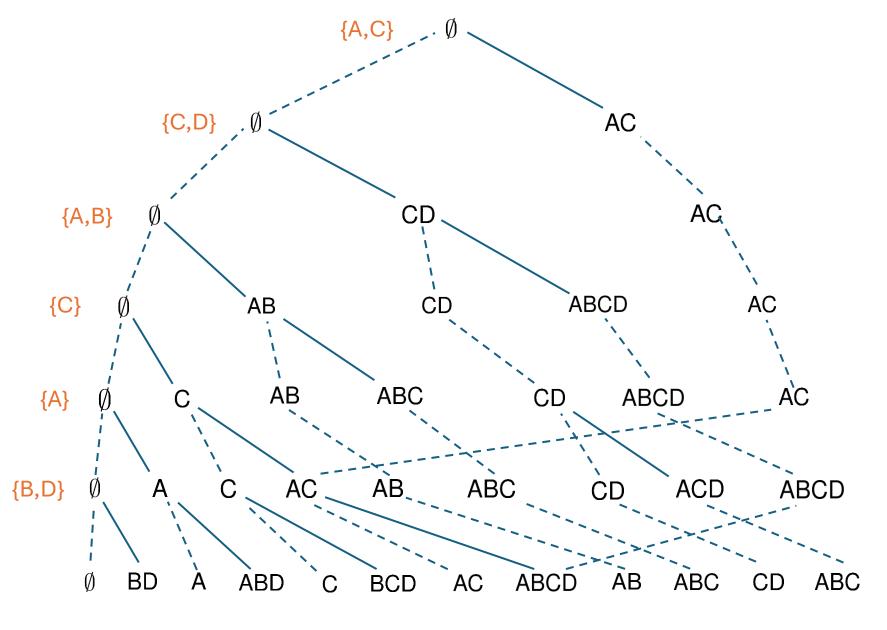


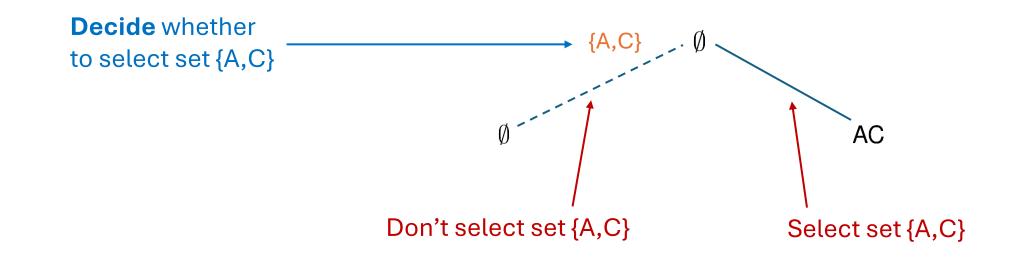
Find a maximum subcollection of sets in which no two sets have common elements.

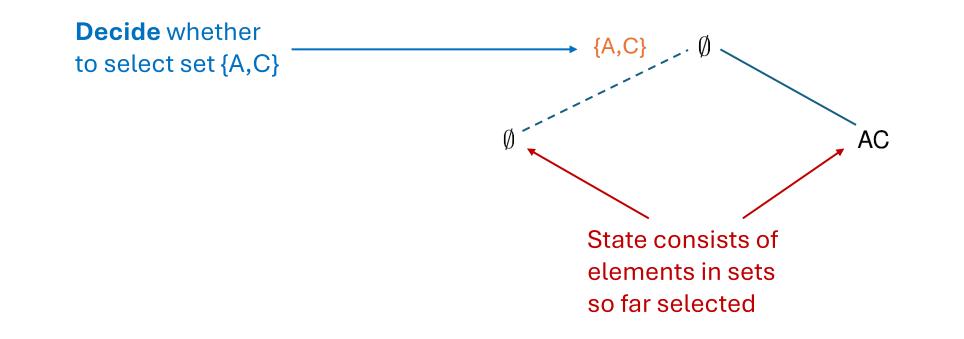
Find a maximum subcollection of sets in which no two sets have common elements.

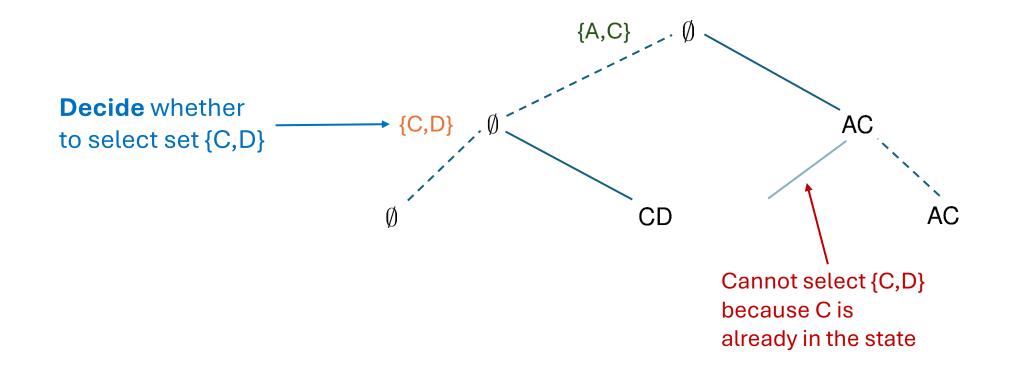
Layers correspond to selection decisions for each set.

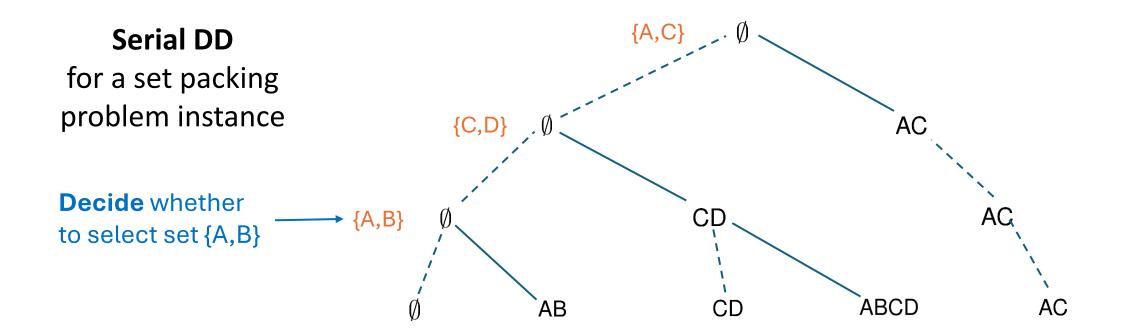
Variables indicate the decisions.

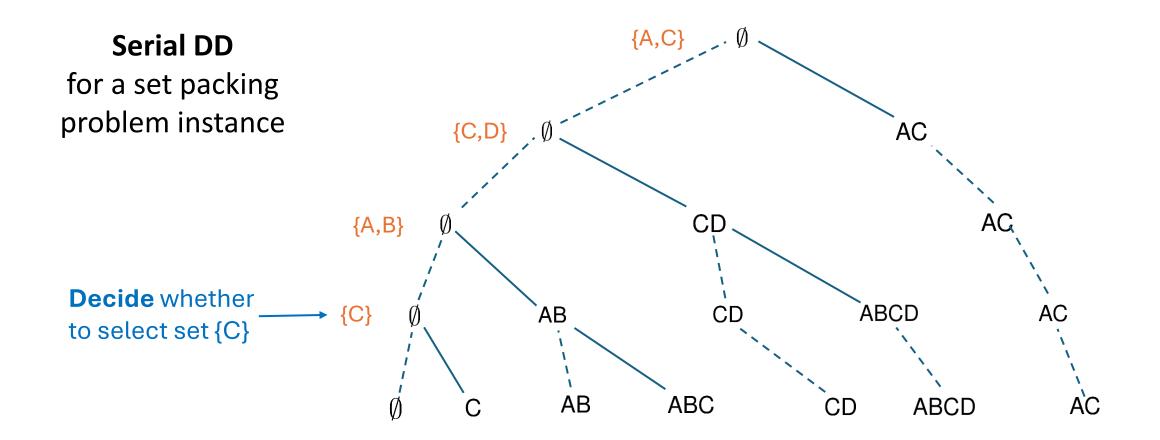


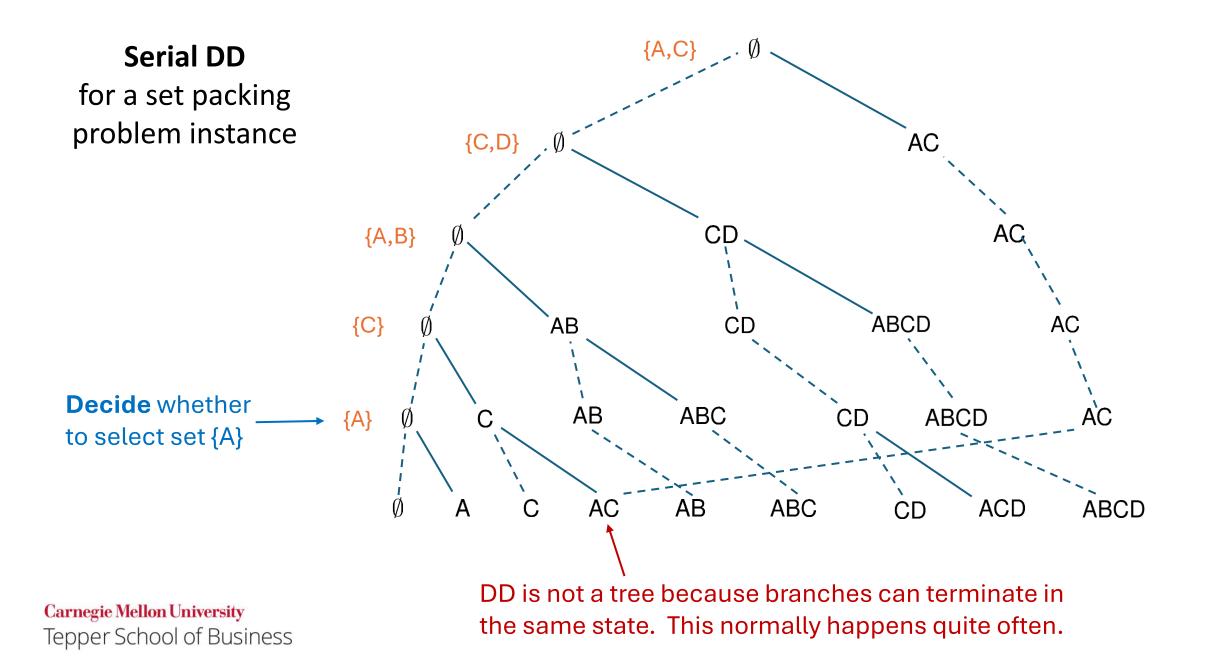


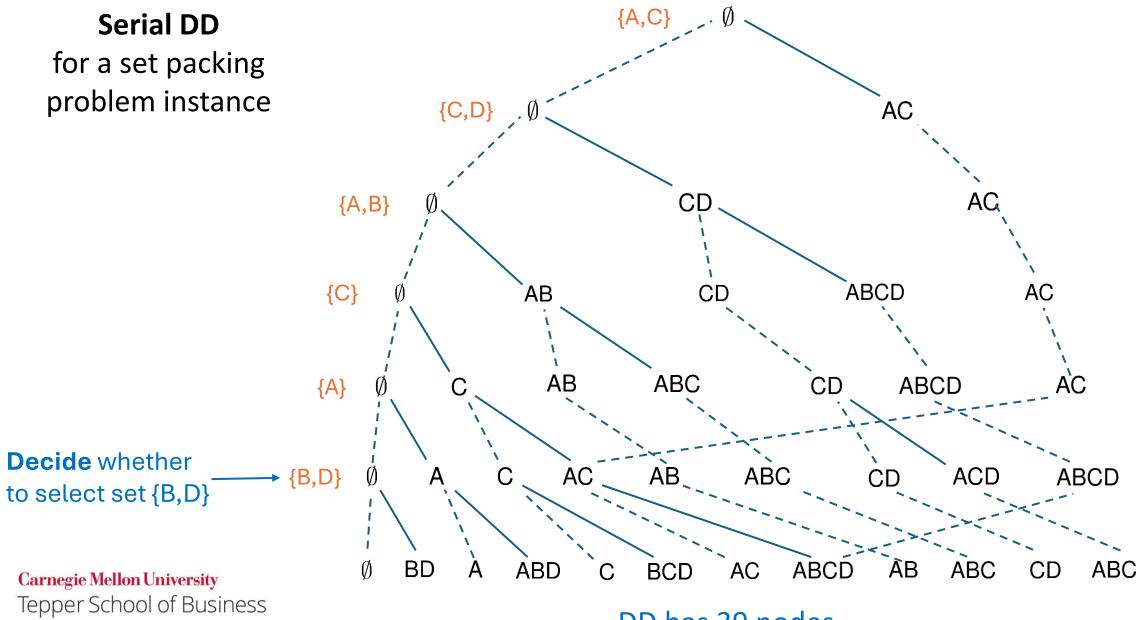






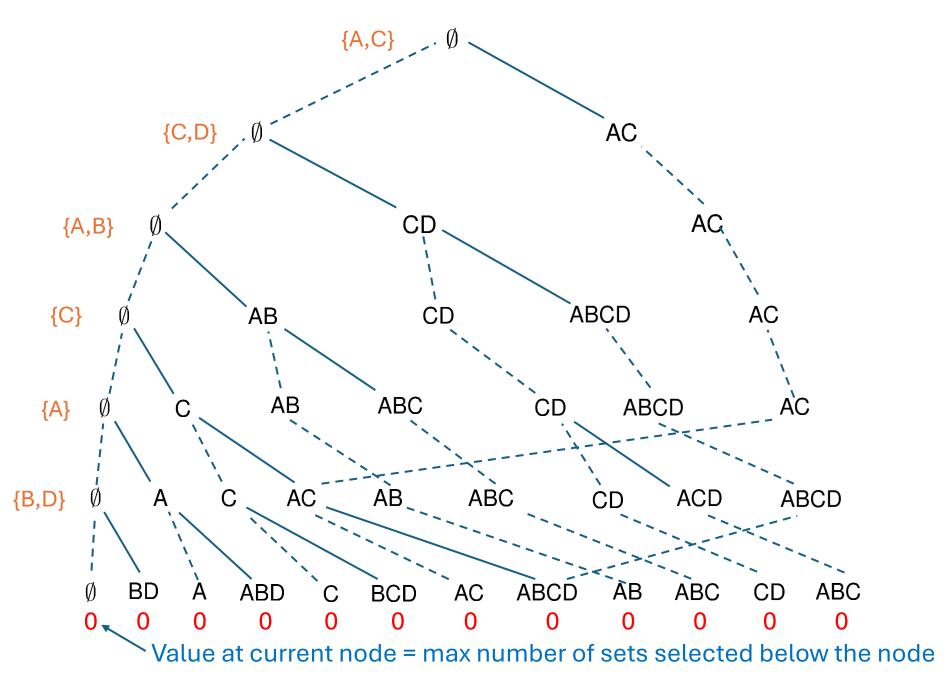


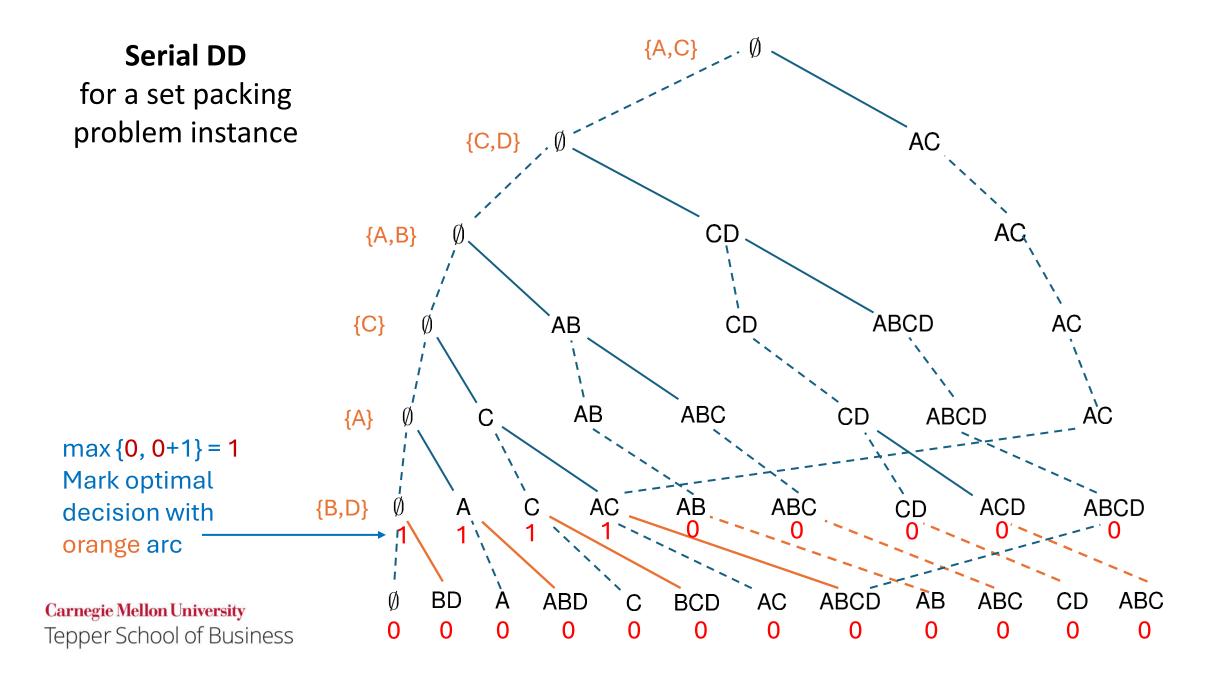


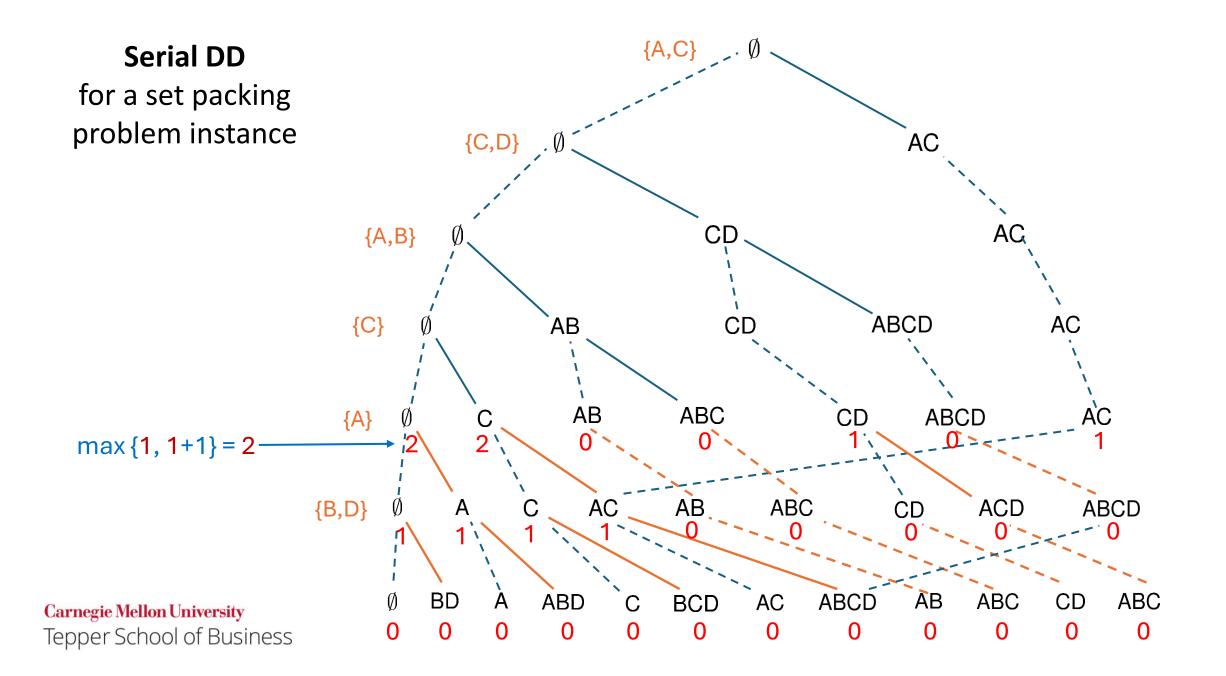


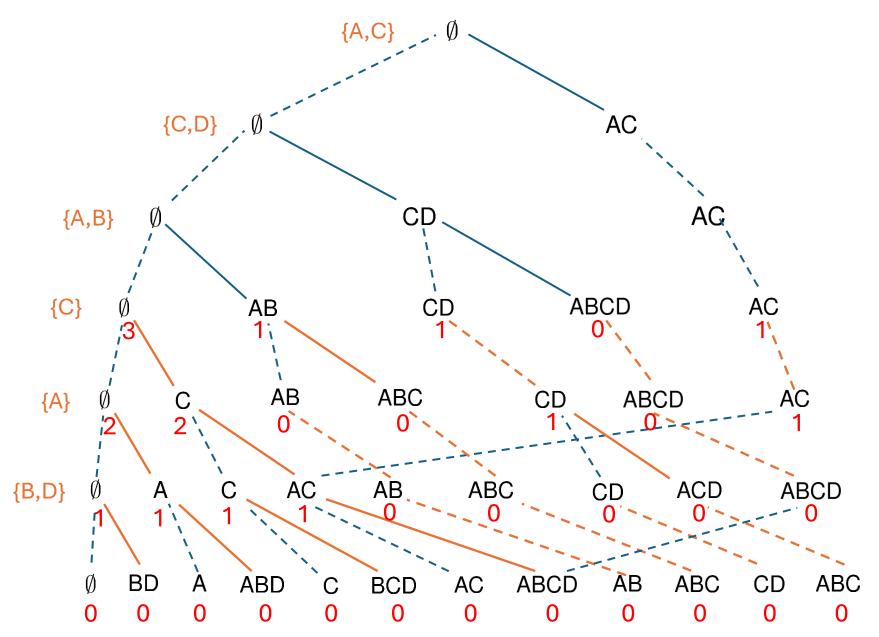
DD has 39 nodes

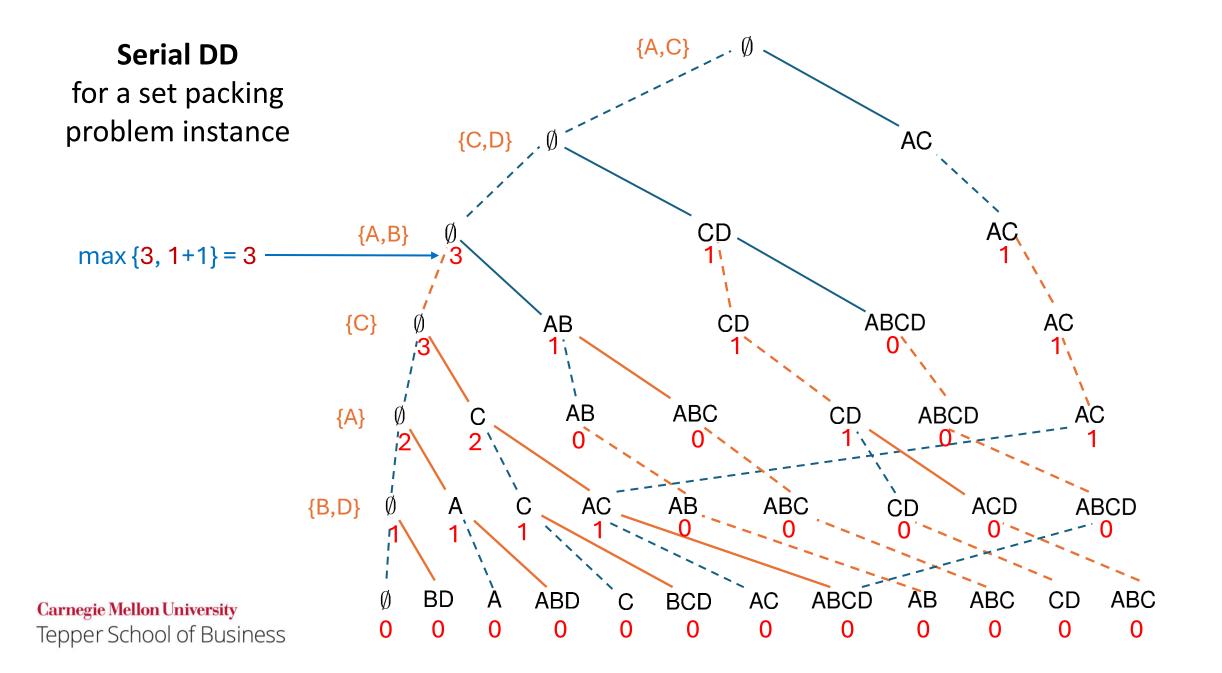
Now find an optimal solution recursively, using a backward pass, as in dynamic programming.

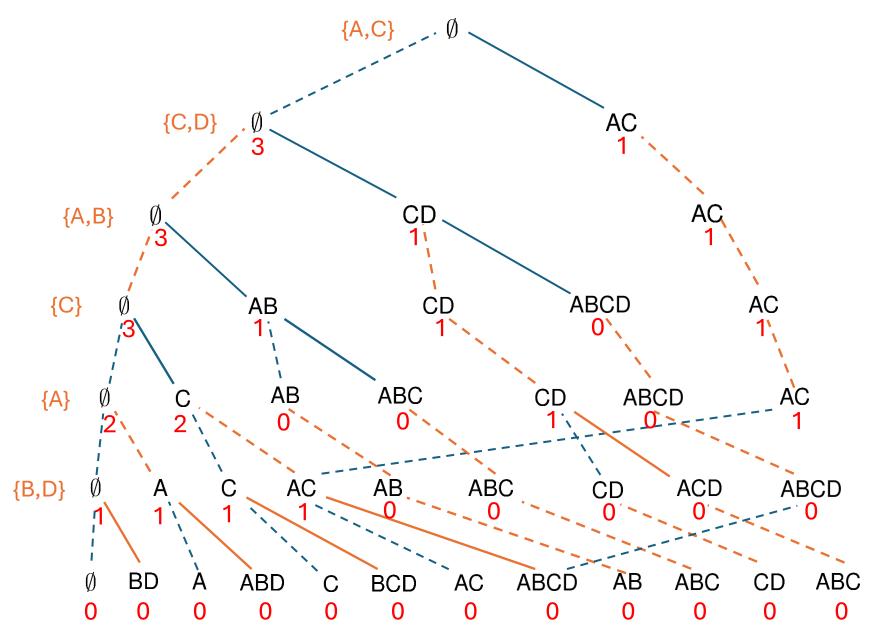




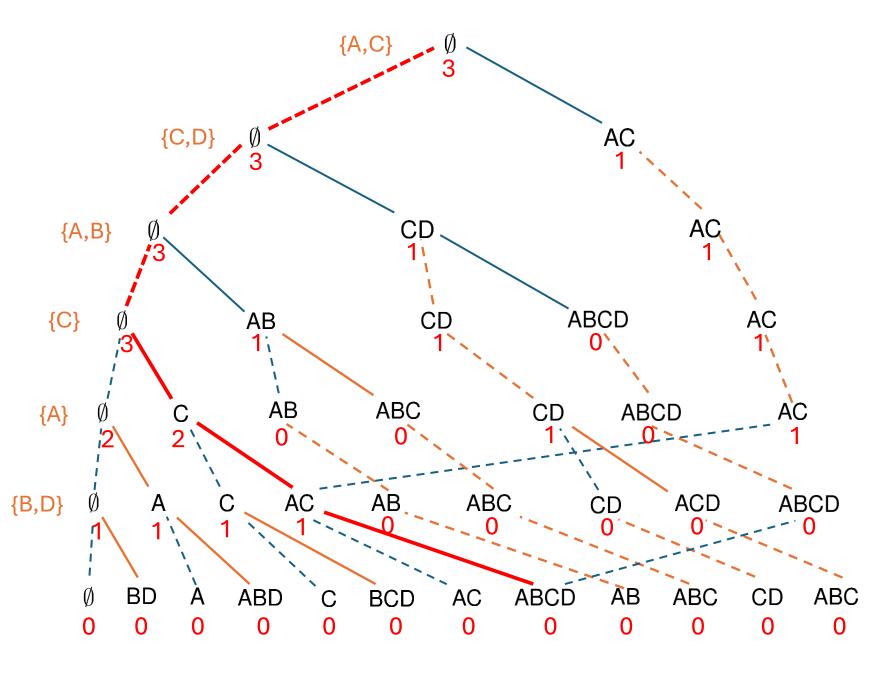








Trace optimal choices top-down to find optimal solution {C} + {A} + {B,D}

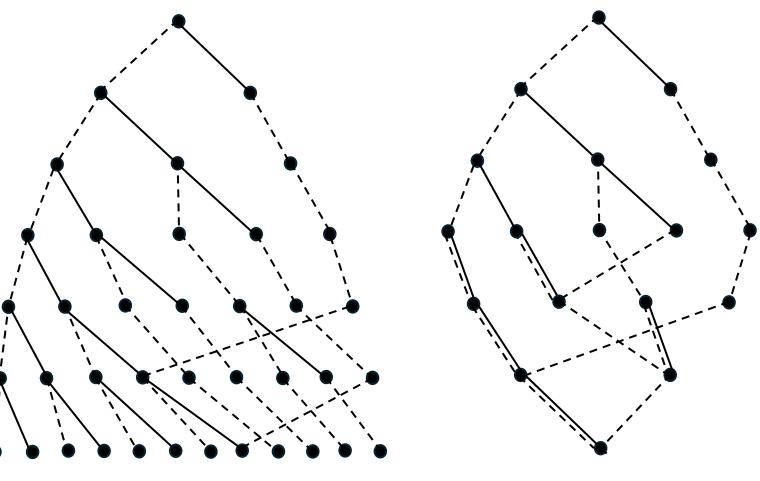


#### Original and reduced serial DDs

For a given variable ordering, a **unique reduced DD** represents a given set of feasible solutions.

Find an **optimal solution** in the reduced DD the same way as before.

There is no need for dynamic programming states.



39 nodes

18 nodes

How does a **DD** differ from a dynamic programming **state transition graph**?

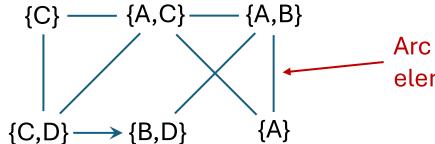
- DD nodes need not be associated with **states**.
- The **reduced DD** can be much **smaller** than the state transition graph.
- Much smaller **relaxed DDs** (obtained by node splitting or merger during top-down compilation) provide **bounds** without solving an LP relaxation.
- Much smaller **restricted DDs** (obtained by deleting arcs during compilation) provide a **primal heuristic**.

## Nonserial Decision Diagrams

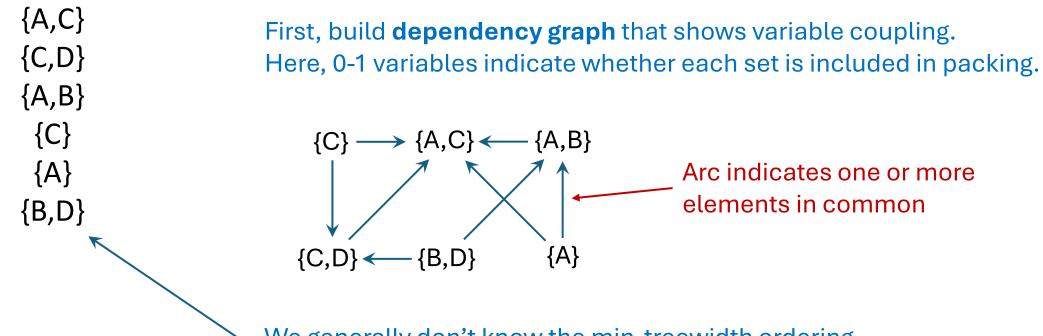
- They exploit structure of problem instances with **small treewidth**.
- Treewidth (with respect to an ordering) = max in-degree of nodes in the induced dependency graph.
- **Complexity** of a problem **instance** is at worst exponential in its minimum **treewidth** over all orderings.
- Instances with small treewidth generate much smaller nonserial DDs and are much easier to solve.

{A,C}
{C,D}
{A,B}
{C}
{C}
{A}
{B,D}

First, build **dependency graph** that shows variable coupling. Here, 0-1 variables indicate whether each set is included in packing.



Arc indicates one or more elements in common



We generally don't know the min-treewidth ordering. As a heuristic, we use a **min-degree ordering**.

{A}

Build tree of layers

for nonserial DD

 $\{C\} \longrightarrow \{A,C\} \longleftarrow \{A,B\}$ 

{B,D}

Remove

{C,D}

Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

{B,D}

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{A,C}

{C,D}

{A,B}

{C}

{A}

{B,D}

Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

 $\{C,D\} \leftarrow \{B,D\} \quad \{A\}$ Induced arc Build tree of layers for nonserial DD

 $\{C\} \longrightarrow \{A,C\} \longleftarrow \{A,B\}$ 

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{A,C}

{C,D}

{A,B}

{C}

{A}

{B,D}

Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

{A,C}
{C,D}
{A,B}
{C}
{C}
{A}
{B,D}

Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

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{A,C}

{C,D}

{A,B}

{C}

{A}

{B,D}

Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

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{A,C}

{C,D}

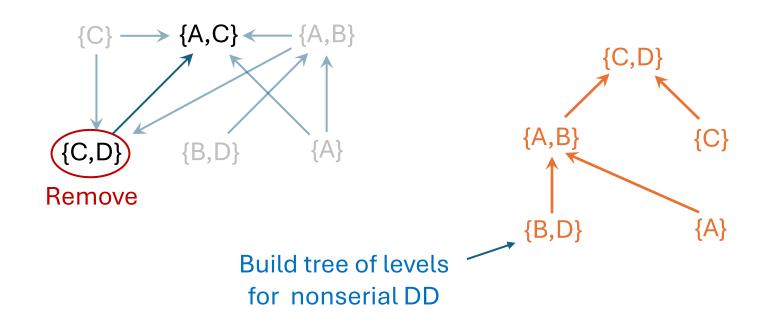
{A,B}

{C}

{A}

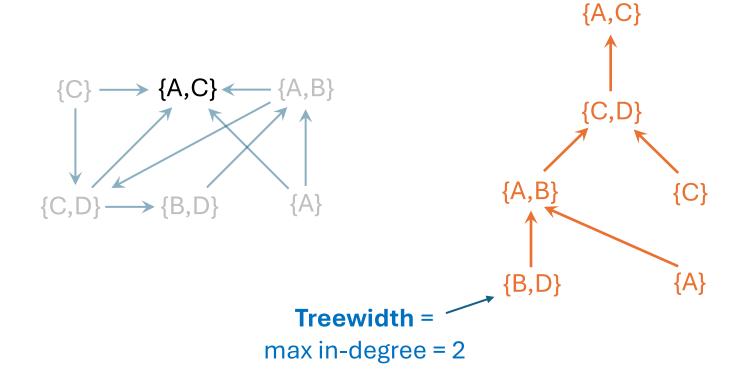
{B,D}

Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

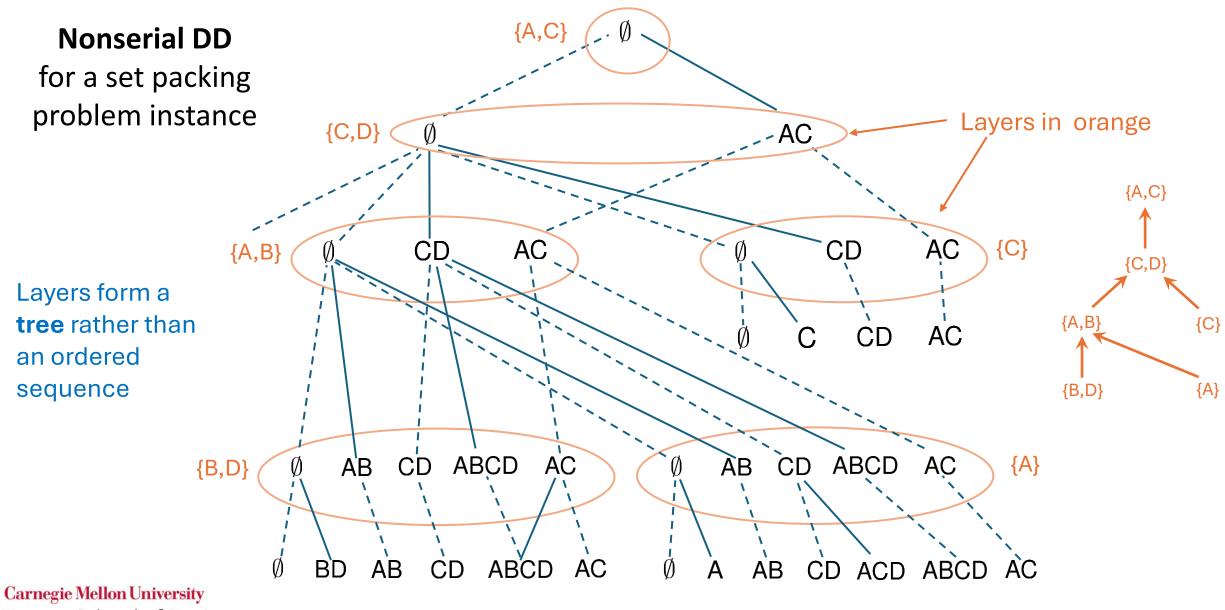


{A,C}
{C,D}
{A,B}
{A,B}
{C}
{A}
{B,D}

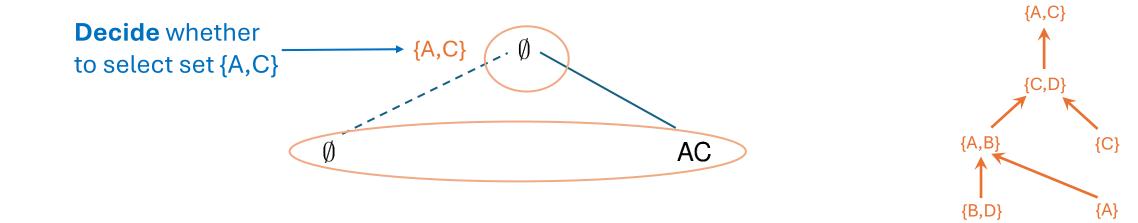
Now, build **induced** dependency graph by removing nodes in order, adding arcs to connect all neighbors.

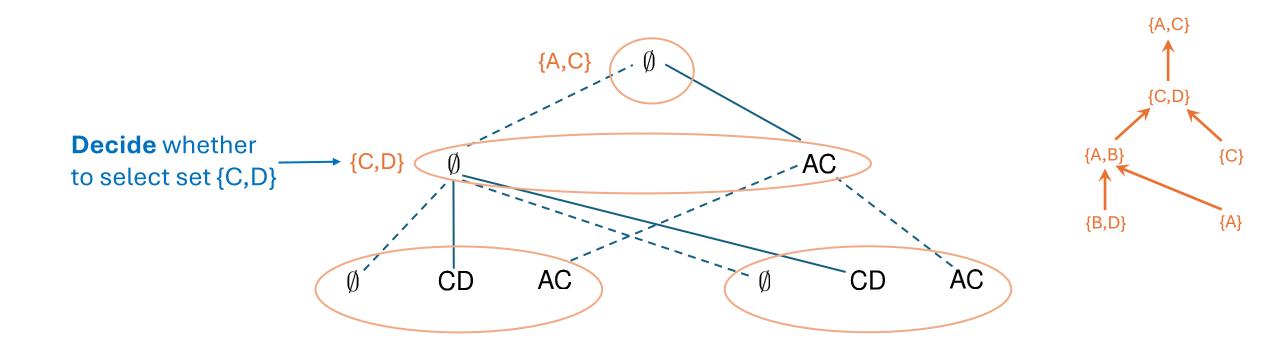


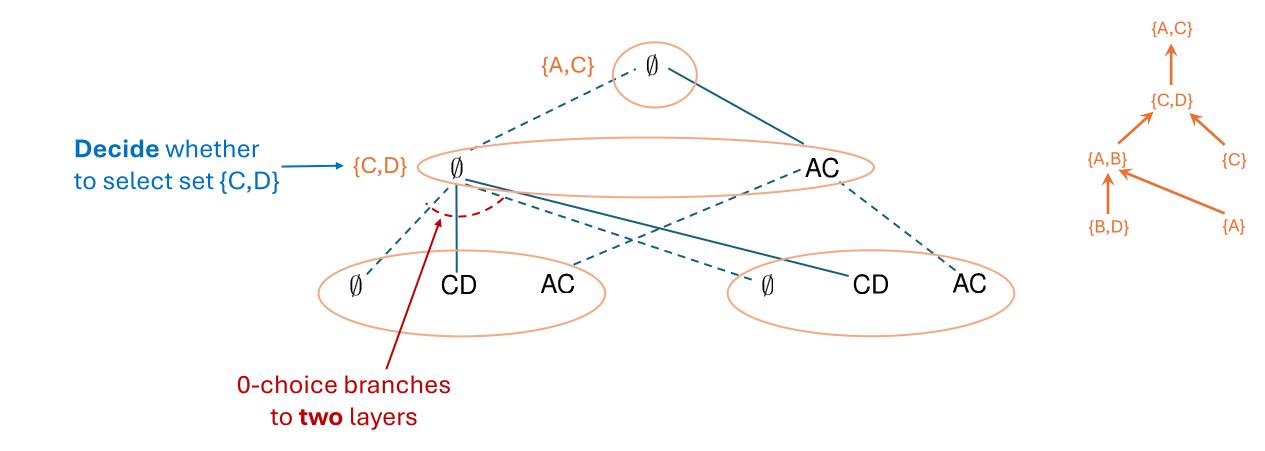
{A,C} {C,D} {A,B} {C} {A} {B,D}

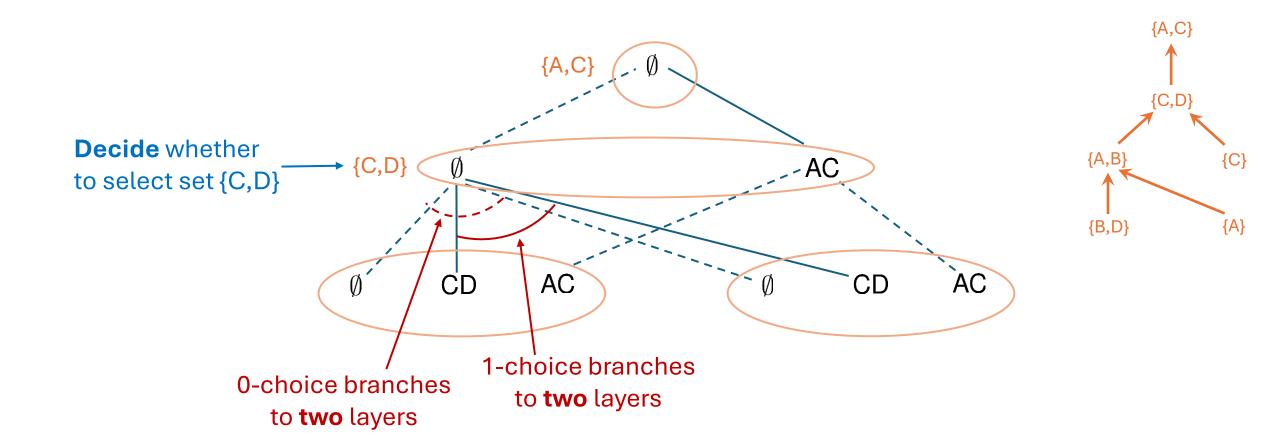


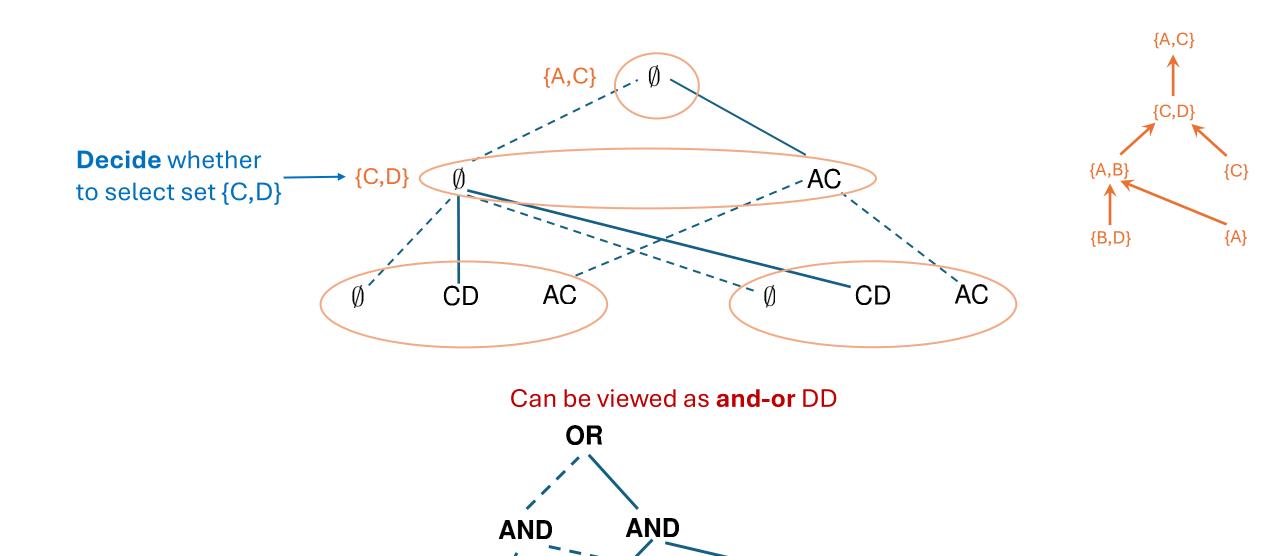
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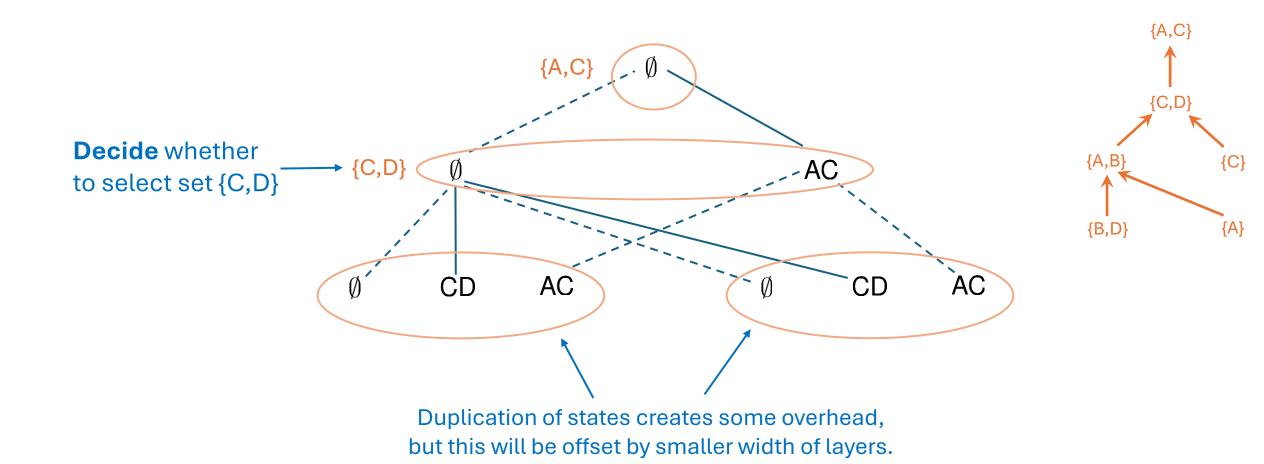


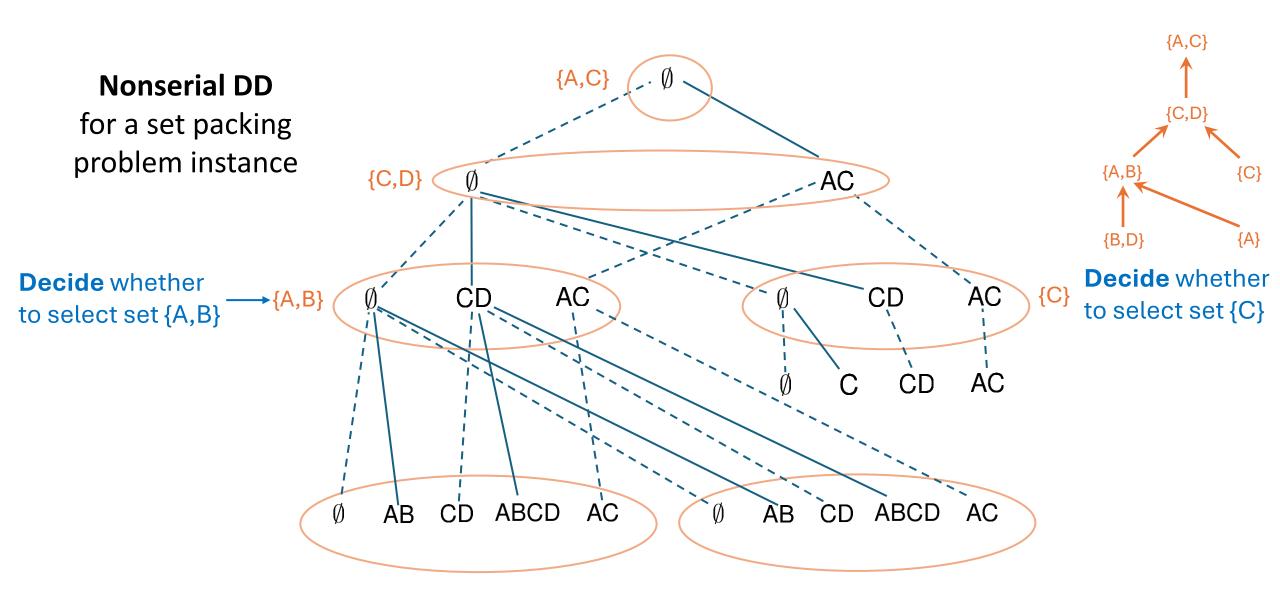
CD

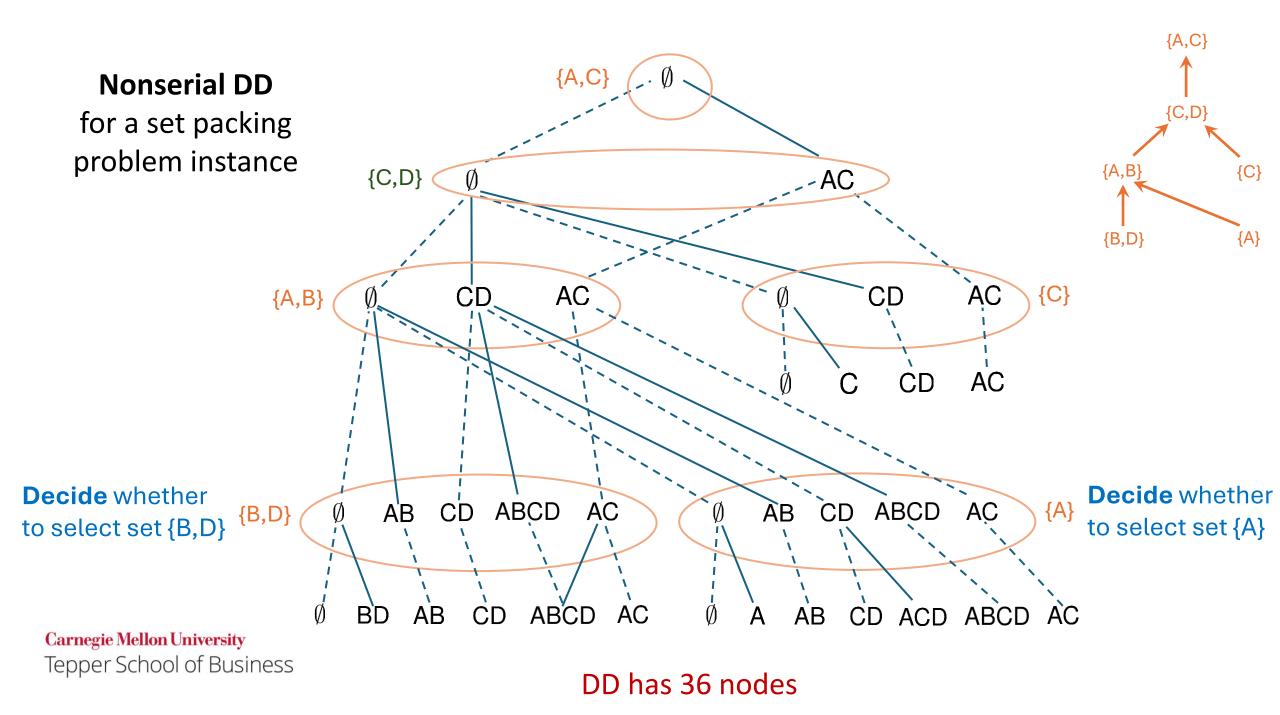
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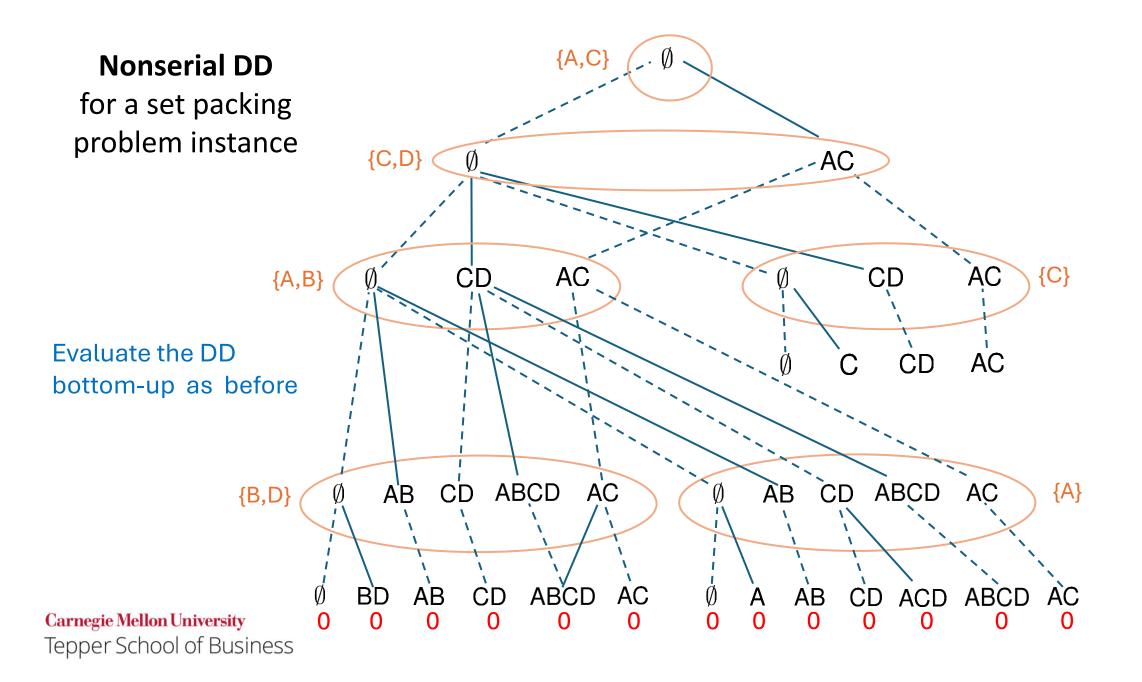
CD

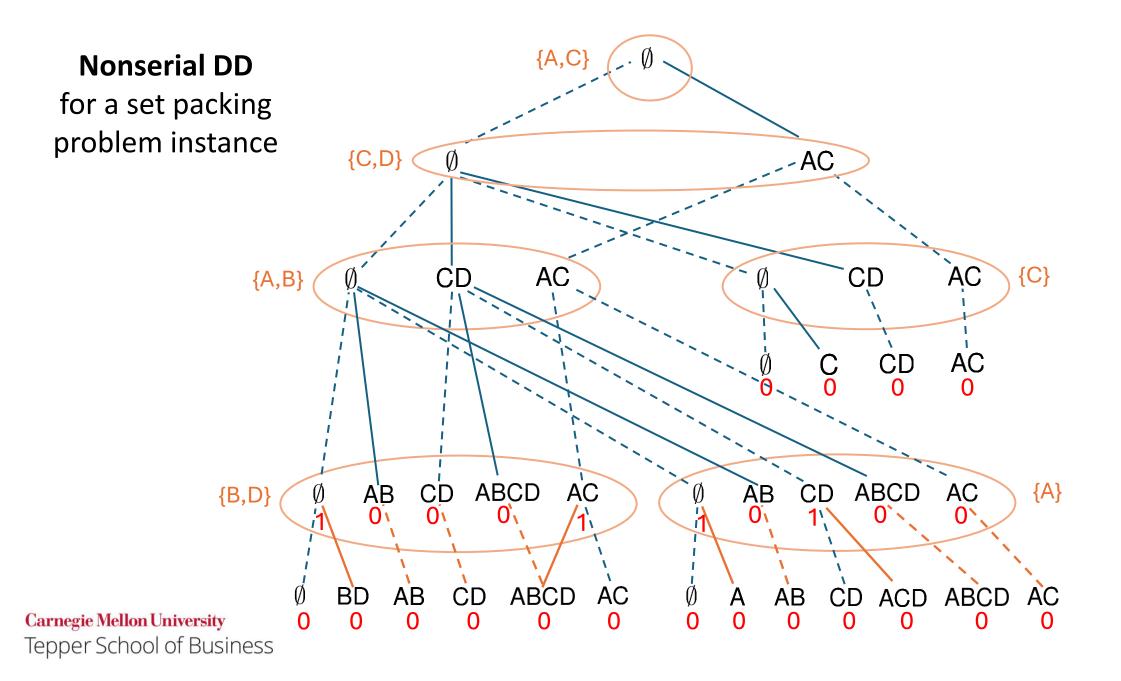
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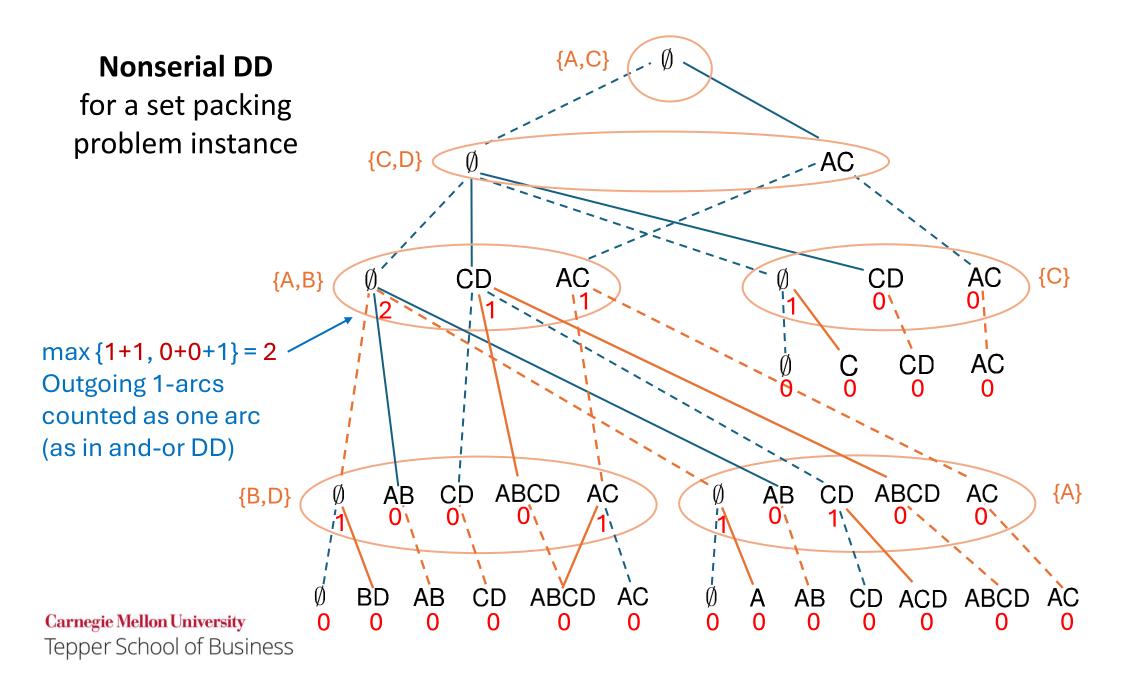


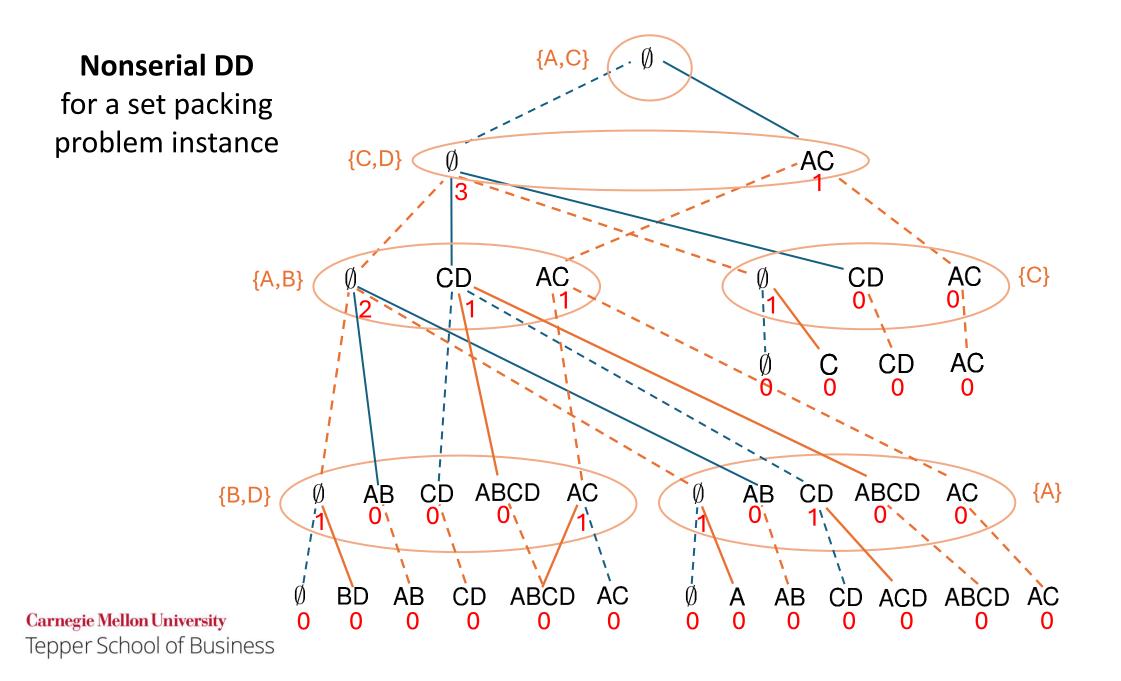


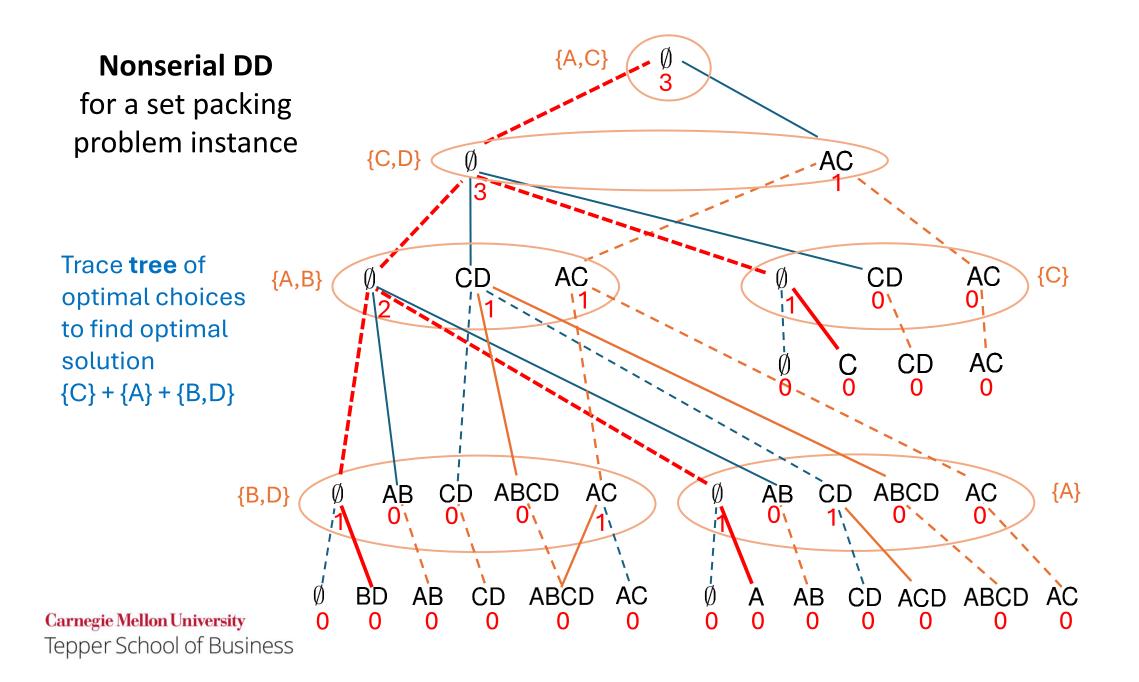


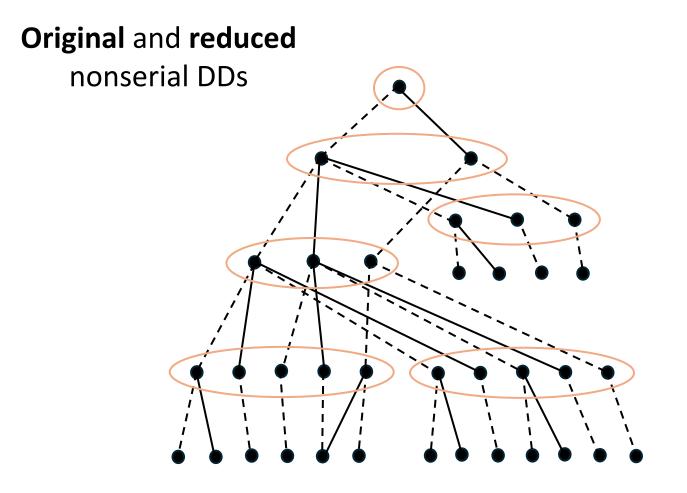


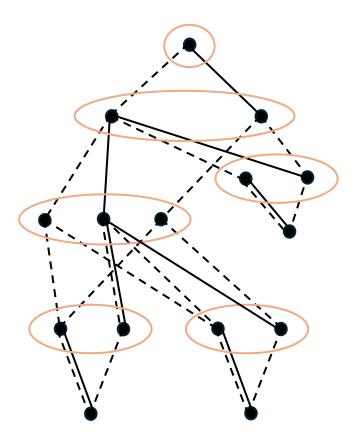












#### 36 nodes

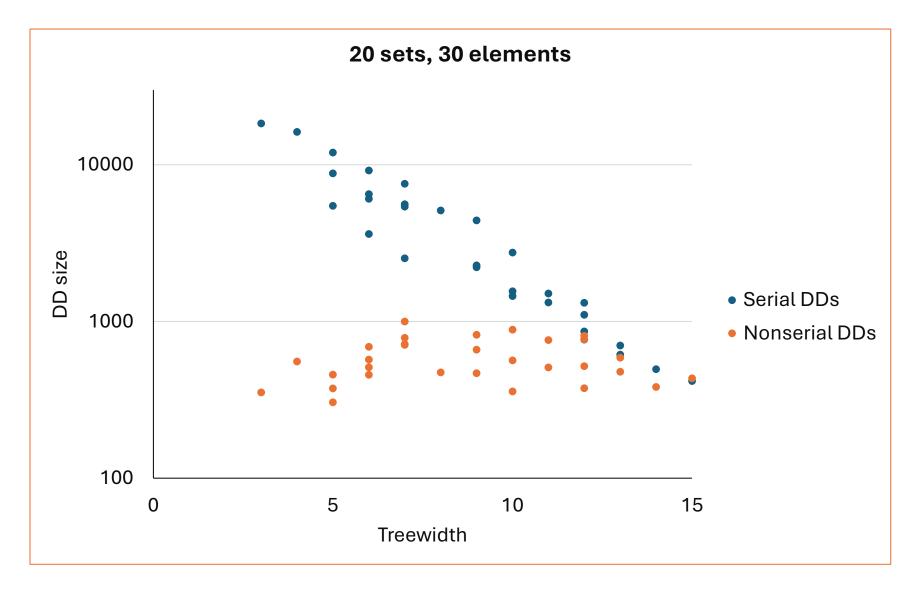
15 nodes

#### **Computational Experiments**

- **Compare size** of non-reduced **serial** and **nonserial DDs** for randomly generated **set packing** instances of various treewidths.
- Use **min-degree ordering** for serial and nonserial DDs, as it benefits both.
- Let each element occur in a given set with **probability p**.
- **Discard** random instances with a **disconnected** dependency graph.
- Use smaller **values of** *p* to get smaller **treewidths**.

Each instance is represented by **two** data points.

Instances with **many** elements per set are easier to solve due to fewer feasible solutions.



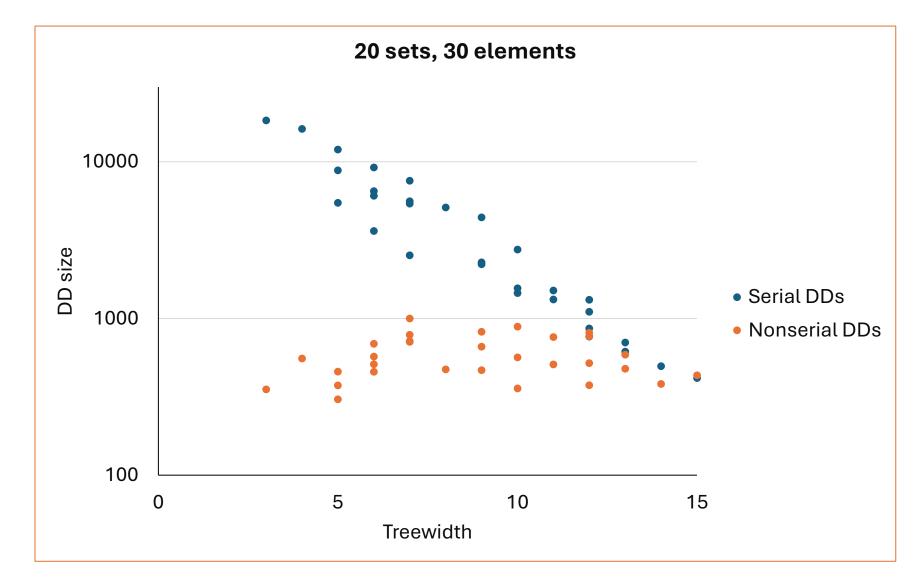
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Smaller bandwidths result in much larger serial DDs (instances are harder).

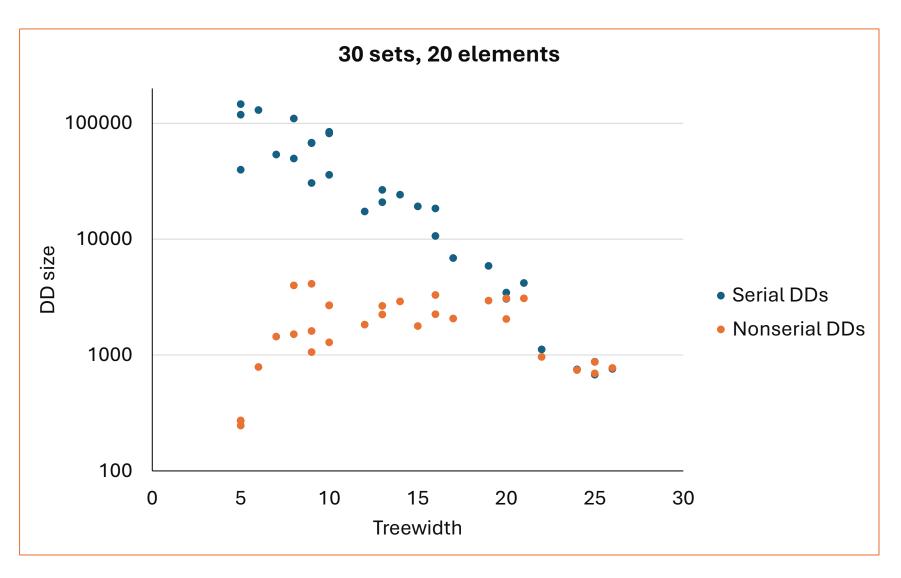
**Nonserial** DD size is fairly **constant.** 

Nonserial DD's exploitation of small bandwidth **offsets** greater difficulty of the instance.

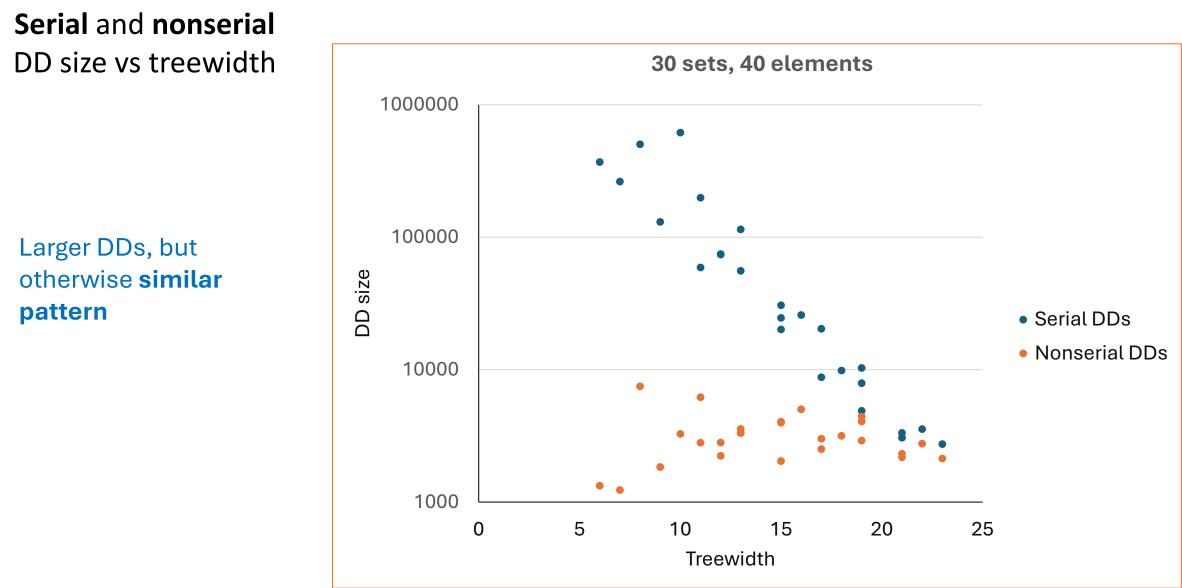
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Similar pattern, except for inverted-U shape of nonserial data points



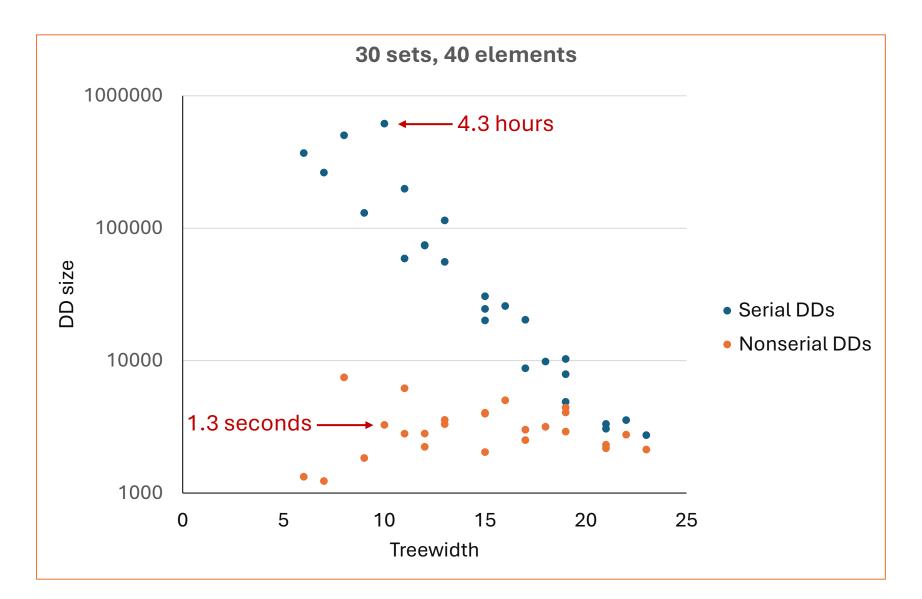
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Difference in **compile time** is even more dramatic than DD size.

Compile time is roughly **quadratic** in max **layer** size.

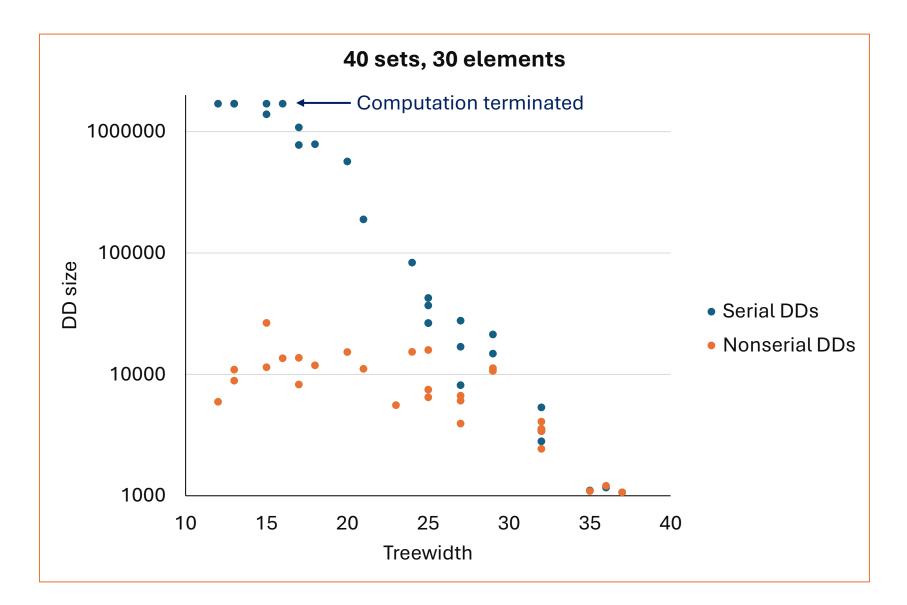
Serial DD layers are much **larger**.



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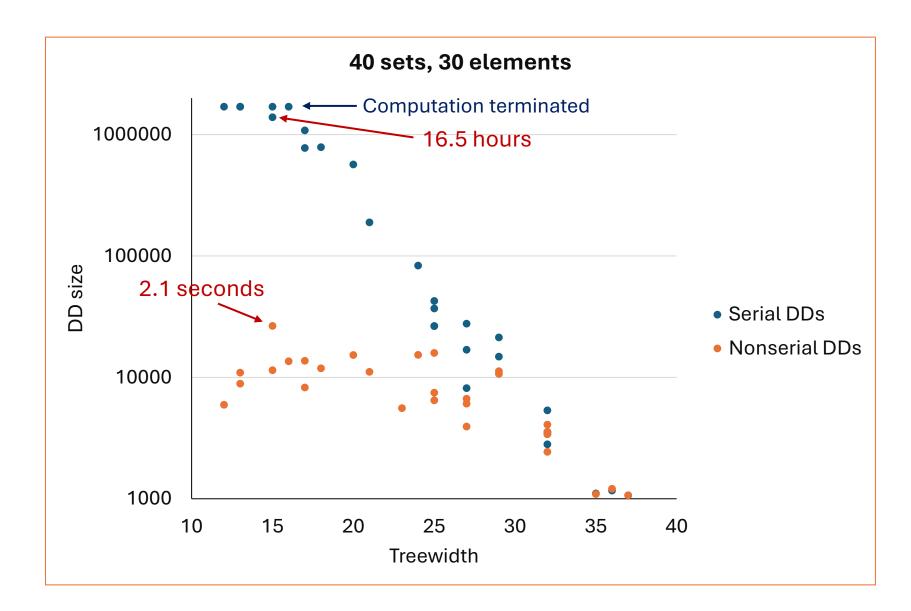
Some **serial** DDs are too large to build.

**Nonserial** DD size again levels off with smaller treewidths



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**Compile time** advantage of nonserial DD is again even greater than **size** advantage.



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Conclusion...

For set packing problems, **nonserial DDs** are **very helpful** when you **need them**, and are **not helpful** when you **don't need them**.

Future research...

Examine other problem classes.

#### Conjectures

- We should **always use nonserial DDs** in DD applications.
- There is **no computational penalty** for doing so.
- There are **enormous computational benefits** when treewidth is limited.
- All DD technologies easily **generalize** to the nonserial case (reduction, relaxation, restriction, flow models)