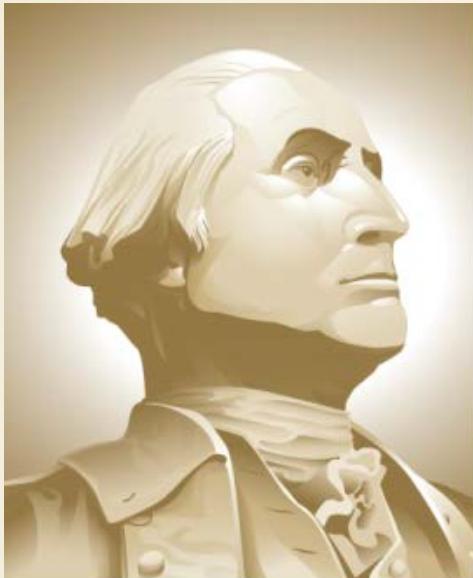


Monitoring Remaining Project Completion Uncertainty, a Bayes Network Approach



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Department of Engineering Management and Systems Engineering

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- Statistical Dependence Elicitation
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- Conclusion

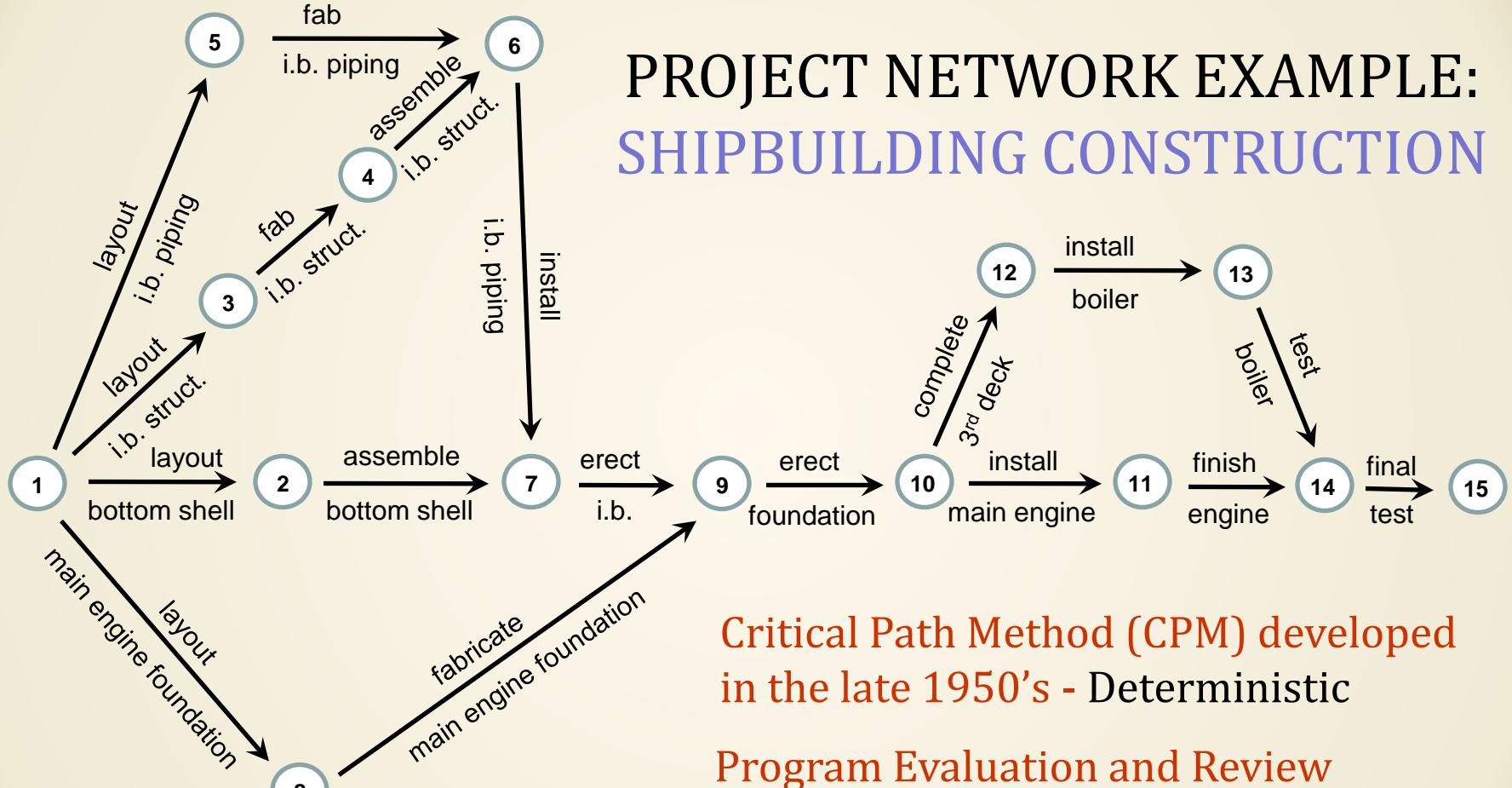
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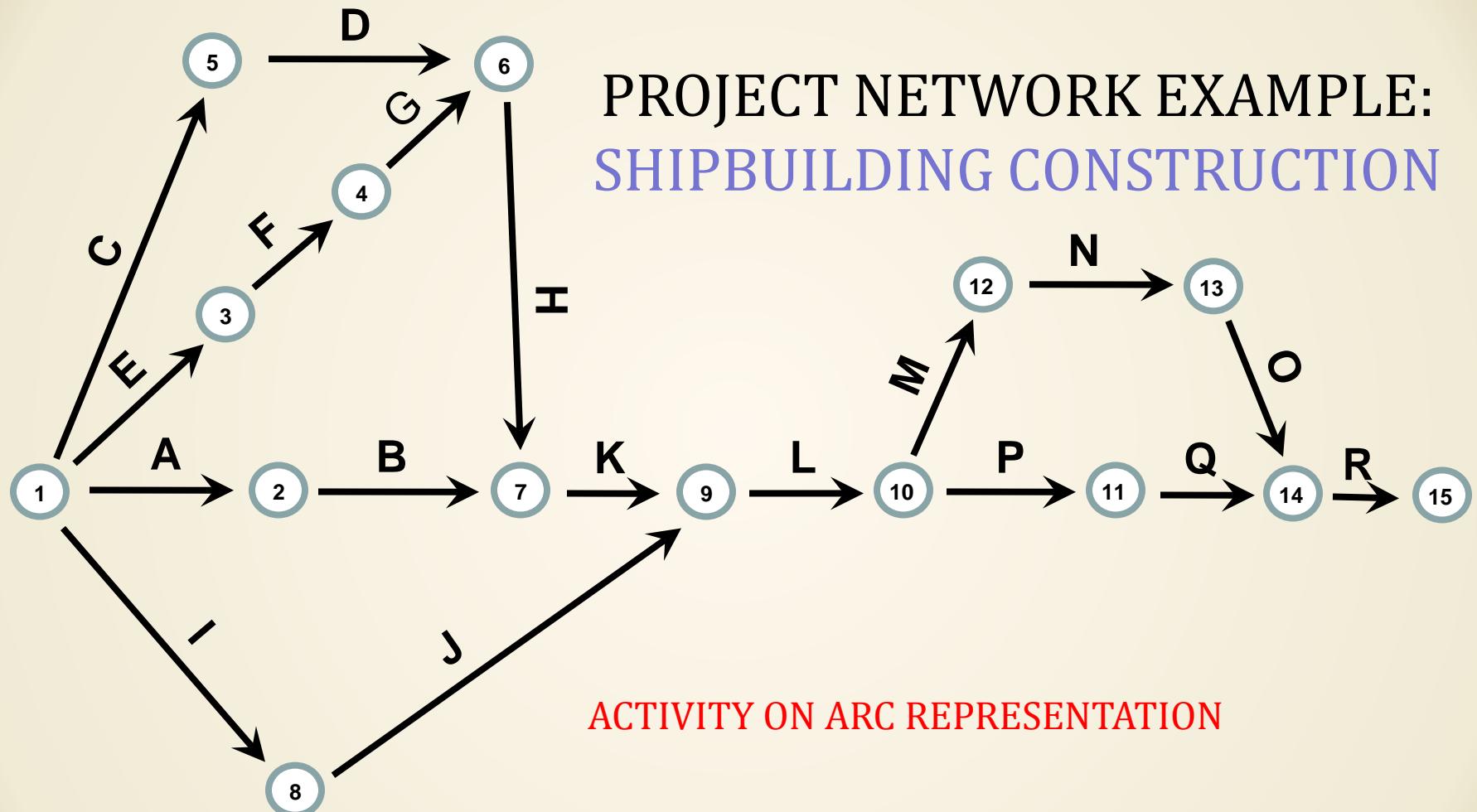
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PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION

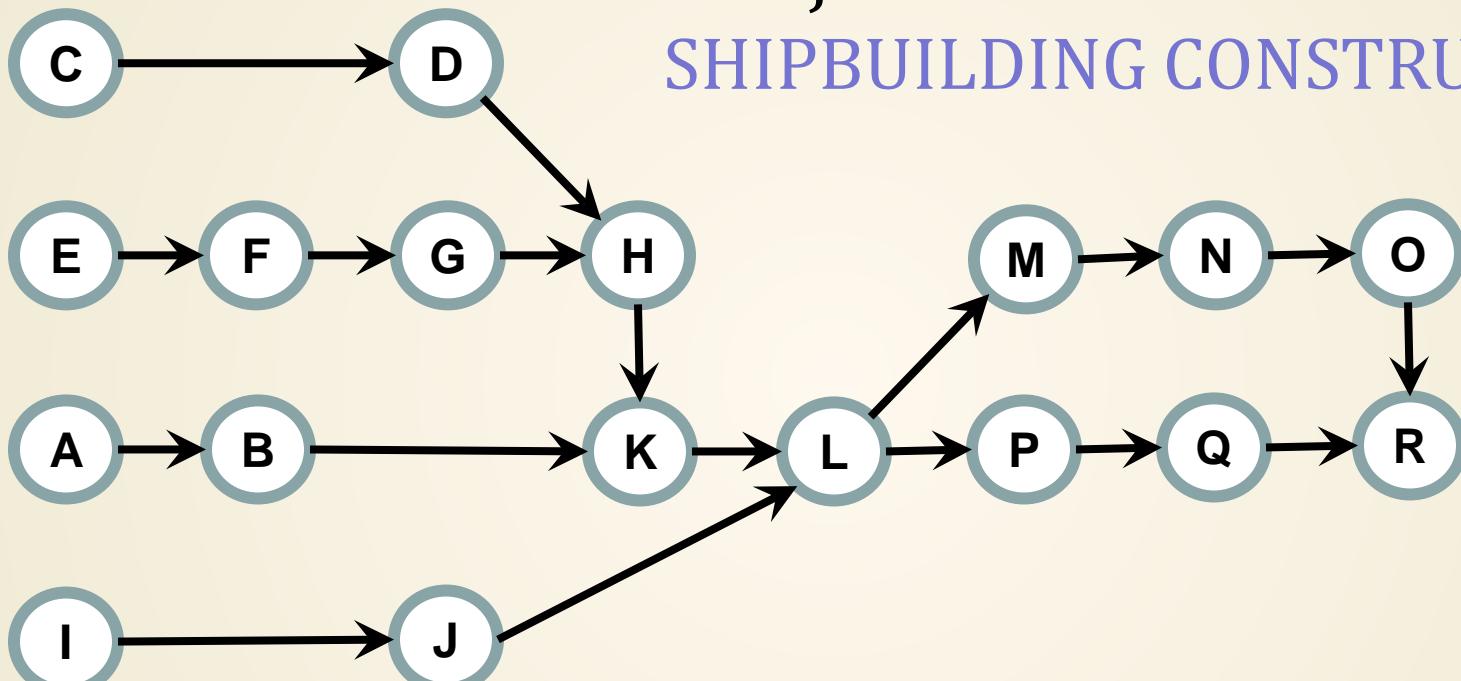


Critical Path Method (CPM) developed in the late 1950's - Deterministic
 Program Evaluation and Review Technique (PERT) developed by Malcolm et al. (1959) – Stochastic CPM

PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



ACTIVITY ON NODE REPRESENTATION

PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION

ID	a	m	b	δ	C(δ)	PERT Variance	Modified PERT Variance
A	22	25	30	0.375	1.250	1.778	2.222
B	35	37	43	0.250	1.143	1.778	2.032
C	19	22	29	0.300	1.194	2.778	3.317
D	4	5	10	0.167	1.032	1.000	1.032
E	23	26	31	0.375	1.250	1.778	2.222
F	16	18	24	0.250	1.143	1.778	2.032
G	11	14	20	0.333	1.222	2.250	2.750
H	6	7	12	0.167	1.032	1.000	1.032
I	25	28	33	0.375	1.250	1.778	2.222
J	33	35	40	0.286	1.181	1.361	1.607
K	27	30	37	0.300	1.194	2.778	3.317
L	6	7	11	0.200	1.080	0.694	0.750
M	4	5	9	0.200	1.080	0.694	0.750
N	6	7	10	0.250	1.143	0.444	0.508
O	9	10	15	0.167	1.032	1.000	1.032
P	6	7	12	0.167	1.032	1.000	1.032
Q	17	20	26	0.333	1.222	2.250	2.750
R	13	15	20	0.286	1.181	1.361	1.607
Average Variance						1.790	

Malcolm
et al. 1959

Herreras
et al. 2011

Traditional Activity Estimates

$$\text{PERT MEAN} = \frac{a + 4m + b}{6}$$

$$\text{PERT VARIANCE} = \frac{(b - a)^2}{36}$$

$$\text{MOD. PERT VARIANCE} = C(\delta) \times \frac{(b - a)^2}{36}$$

$$\delta = \frac{m - a}{b - a}, C(\delta) = \frac{5}{7} + \frac{16}{7} \times \delta(1 - \delta)$$

PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION

Malcolm et al. (1959) assumed statistical independence between activity durations

This is a specious assumption however!

- Imagine activities that have to be completed under the open sky
 - Imagine activities that require the use of a single crane
 - Imagine activities completed by the same subcontractor
- Approaches thus far that have tried to relax the independence assumption unfortunately suffer from high parameter specification burden in a problem context that already suffers from that “ailment”
- Looking to relax that independence assumption in a “pragmatic” manner that builds on Malcolm’s et al. (1959) work

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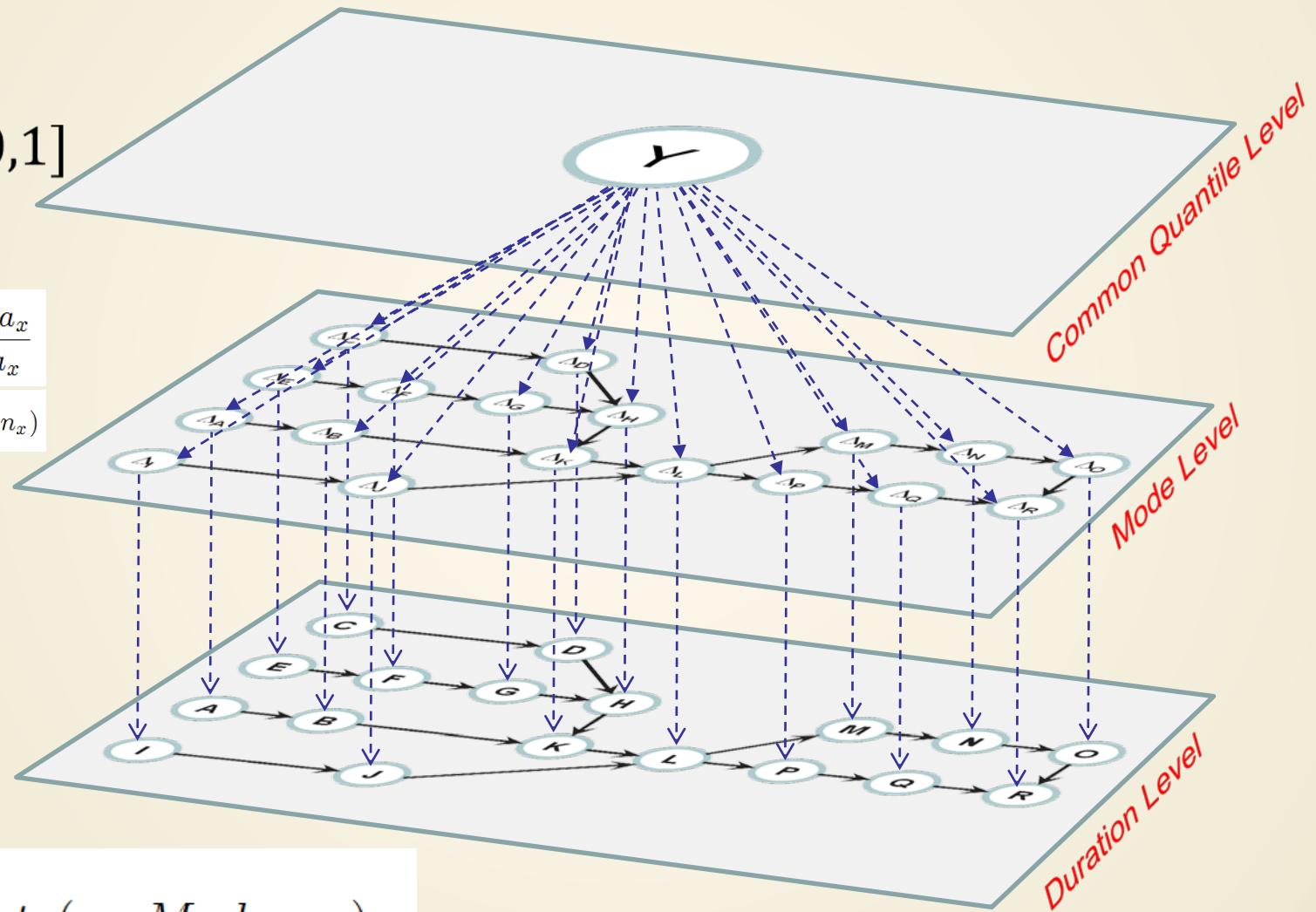
Bayesian Network Dependence Model for Project Risk Analysis

$$Y \sim U[0,1]$$

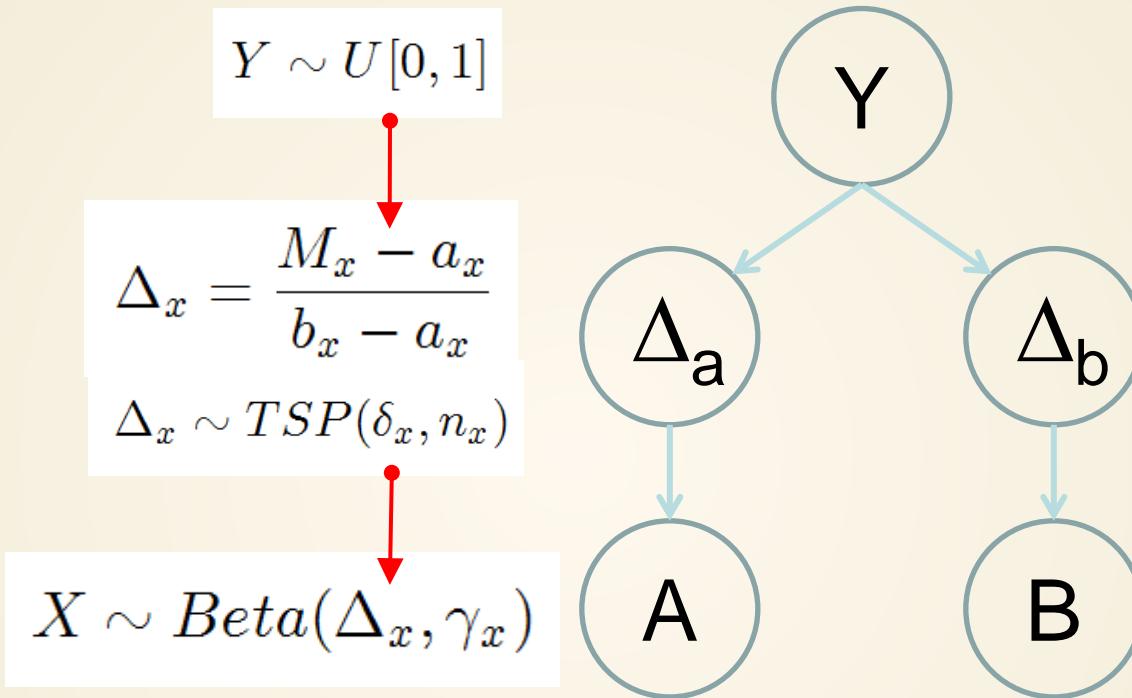
$$\Delta_x = \frac{M_x - a_x}{b_x - a_x}$$

$$\Delta_x \sim TSP(\delta_x, n_x)$$

$$X \sim Beta(a_x, M_x, b_x, \gamma_x)$$



How does dependence materialize throughout the Bayesian Network?



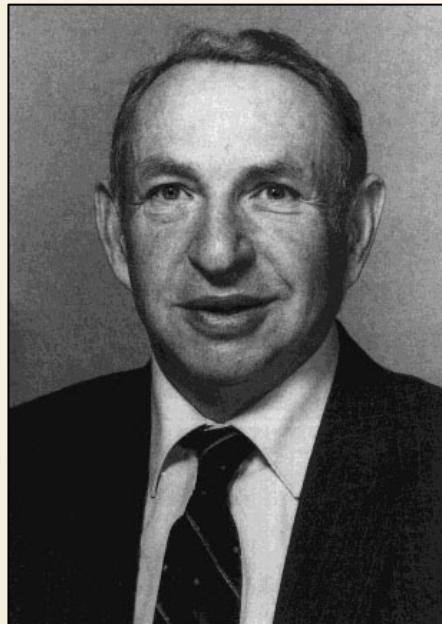
Mode parameterization of Beta Distribution

$$g_X(x|\Delta_x, \gamma_x) = \frac{x^{\gamma_x \Delta_x} (1-x)^{\gamma_x(1-\Delta_x)}}{\mathbb{B}(\gamma_x \Delta_x + 1, \gamma_x(1-\Delta_x) + 1)}$$

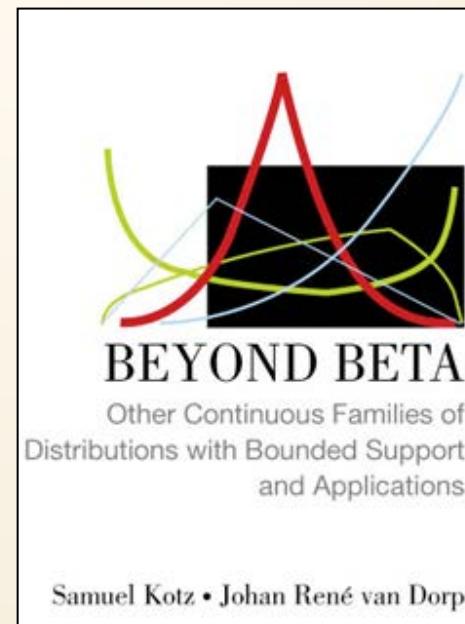
How does dependence materialize throughout the Bayesian Network?

**Two Sided Power Density of
Mode Relative Distance Δ_x**

$$f_{\Delta_x}(u|\delta_x, n_x) = n_x \times \begin{cases} \left(\frac{u}{\delta_x}\right)^{n_x-1}, & 0 \leq u \leq \delta_x, \\ \left(\frac{1-u}{1-\delta_x}\right)^{n_x-1}, & \delta_x \leq u \leq 1. \end{cases}$$



S. Kotz 1930 – 2010



2004

Some Two-Sided Power Distribution Properties

Cumulative Distribution Function:

$$F_{\Delta_x}(u|\delta_x, n_x) = \begin{cases} \delta_x \left(\frac{u}{\delta_x}\right)^{n_x}, & 0 \leq u \leq \delta_x, \\ 1 - (1 - \delta_x) \left(\frac{1-u}{1-\delta_x}\right)^{n_x}, & \delta_x \leq u \leq 1, \end{cases}$$

Quantile Function:

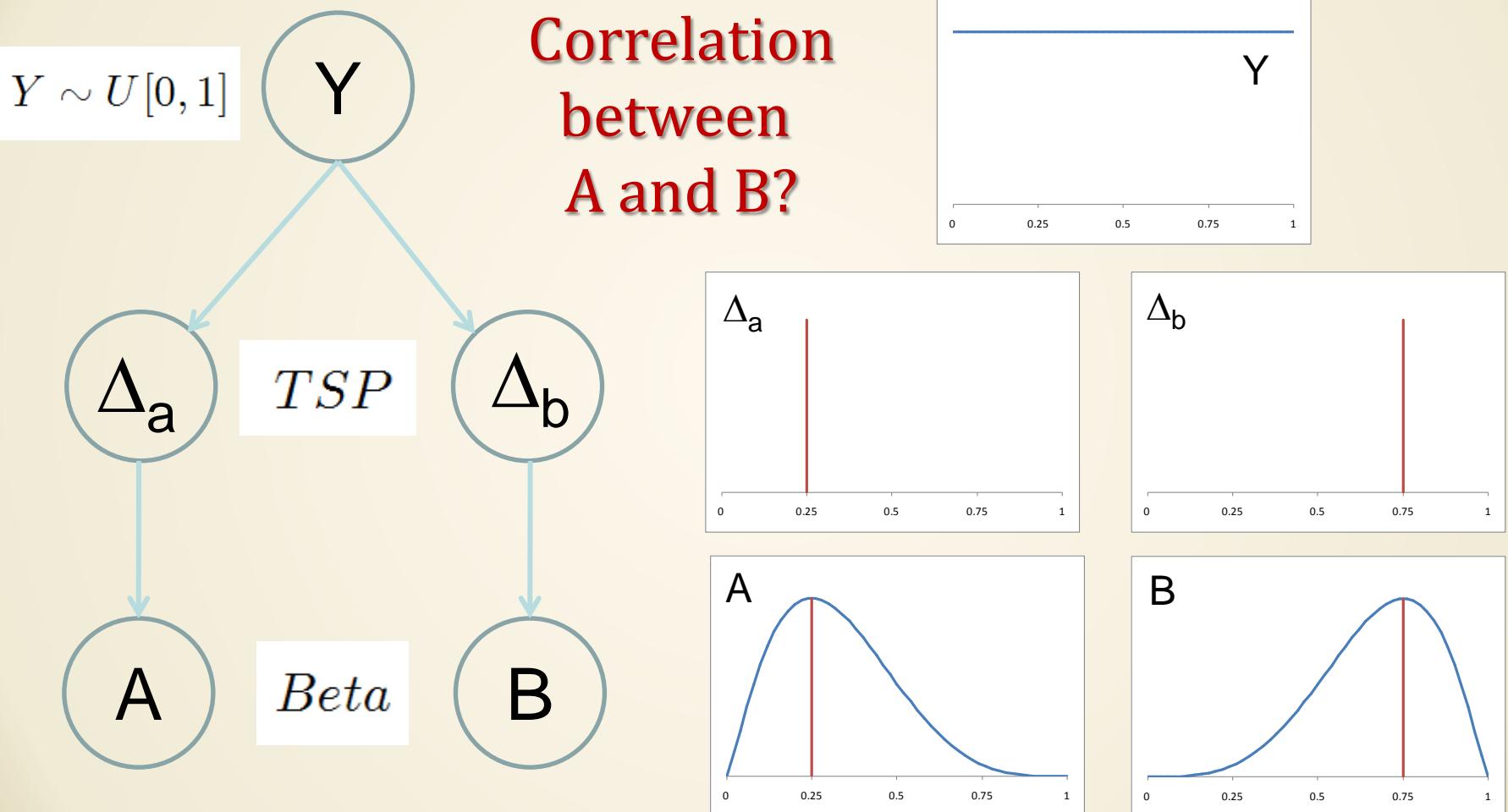
$$F_{\Delta_x}^{-1}(y|\delta_x, n_x) = \begin{cases} \delta_x \left(\frac{y}{\delta_x}\right)^{1/n_x}, & 0 \leq y \leq \delta_x, \\ 1 - (1 - \delta_x) \left(\frac{1-y}{1-\delta_x}\right)^{1/n_x}, & \delta_x \leq y \leq 1. \end{cases}$$

Conclusion:

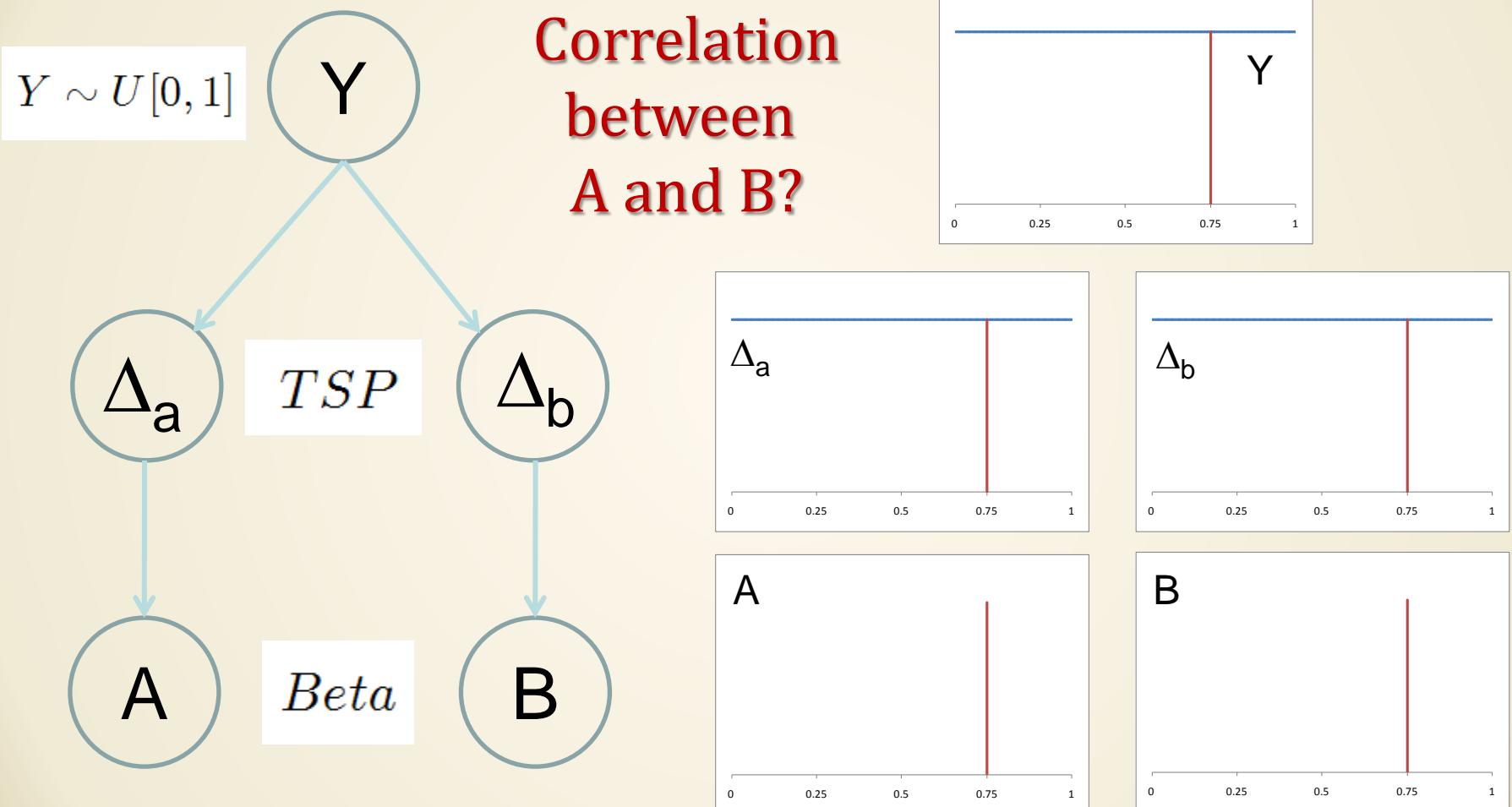
$$F_{\Delta_x}^{-1}(y|\delta_x, n_x) = F_{\Delta_x}(y|\delta_x, 1/n_x).$$

QF and CDF are of the same functional form!

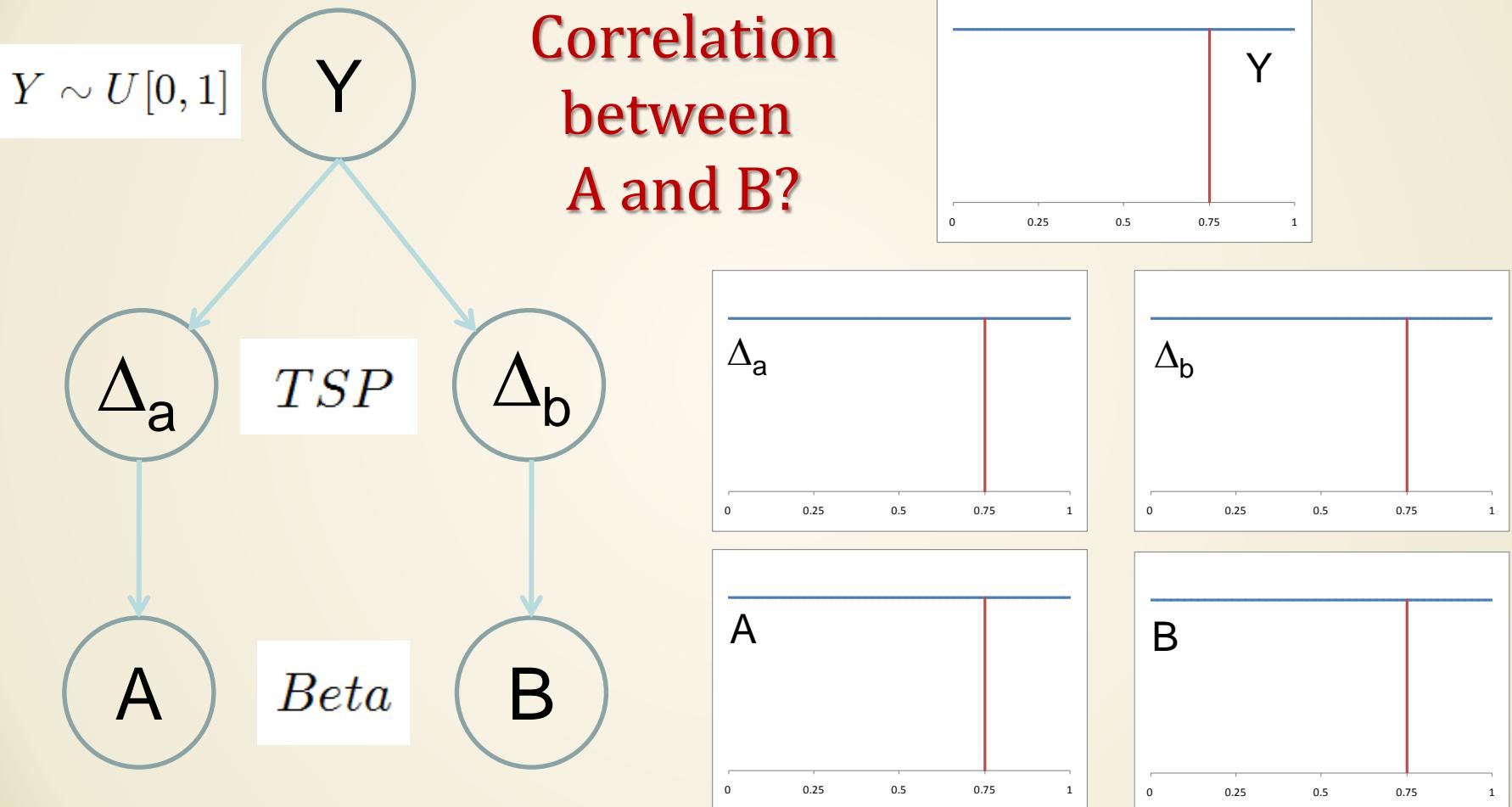
How does dependence materialize throughout this Bayesian Network?



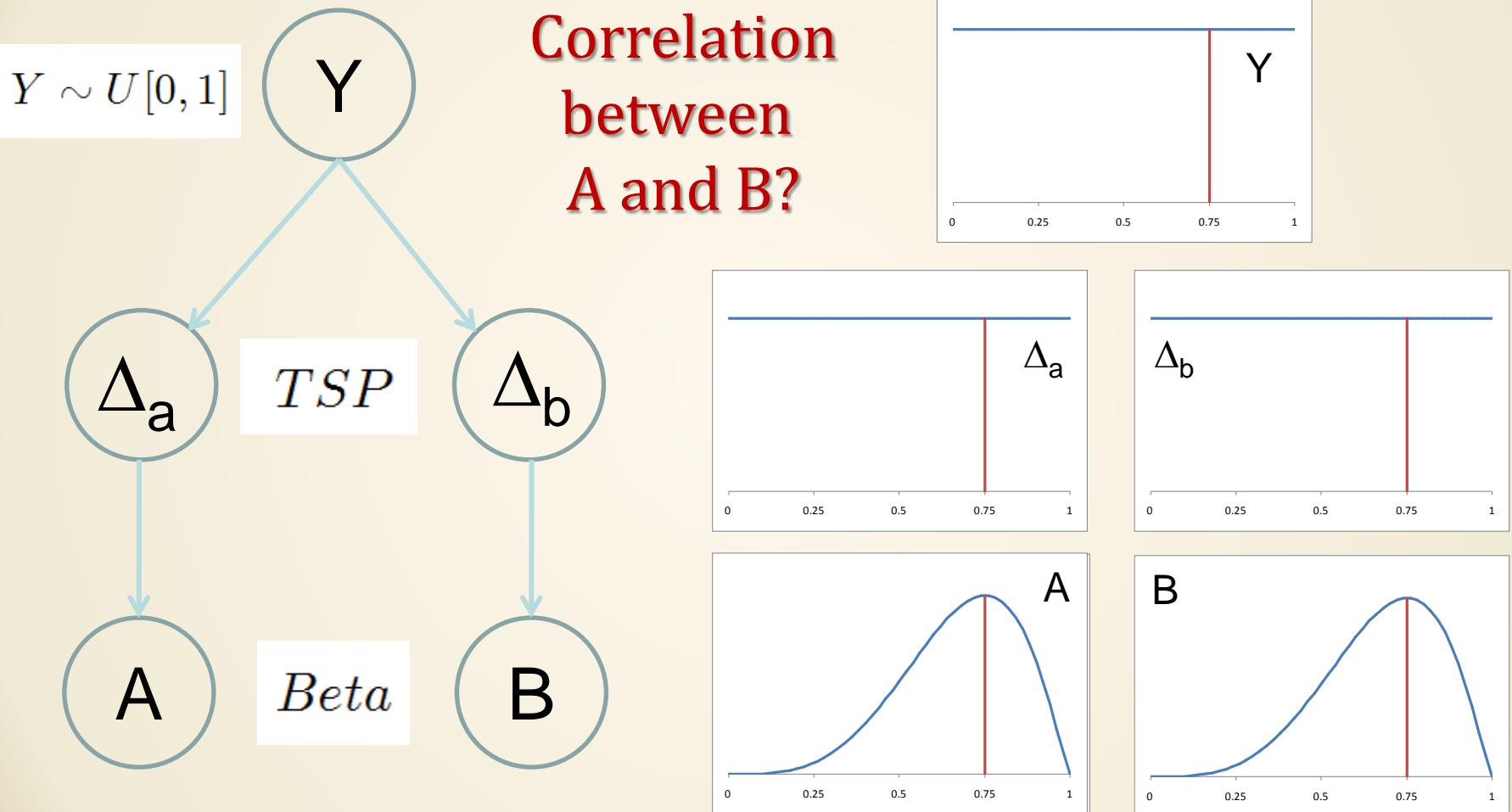
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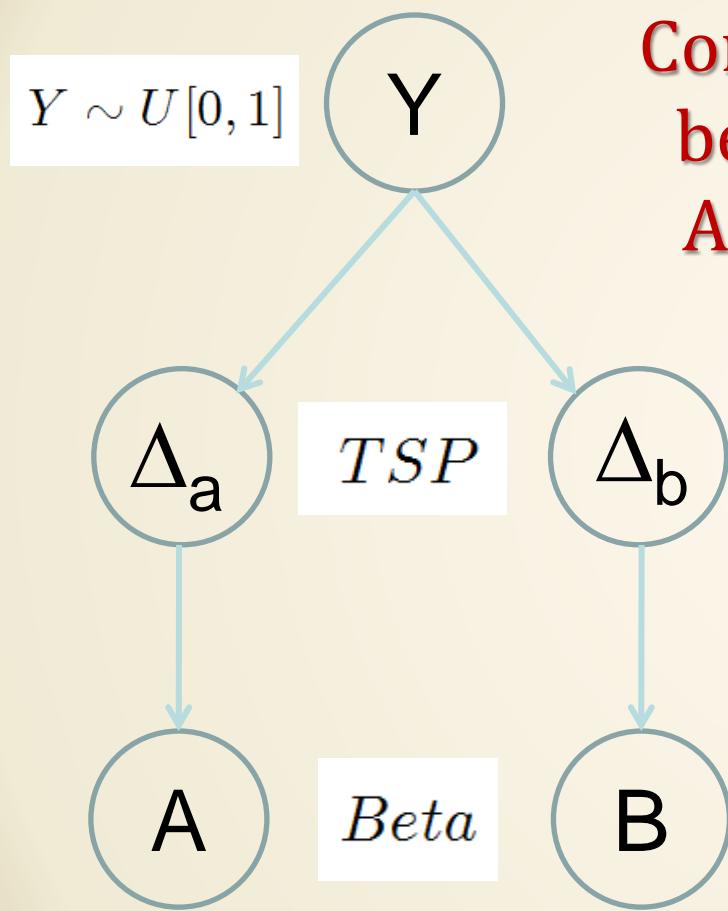
How does dependence materialize throughout this Bayesian Network?



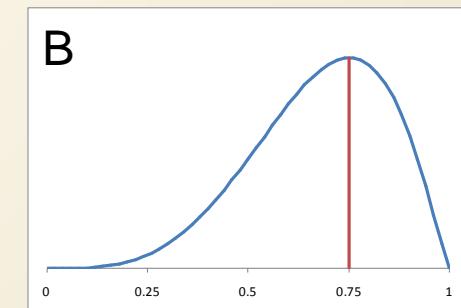
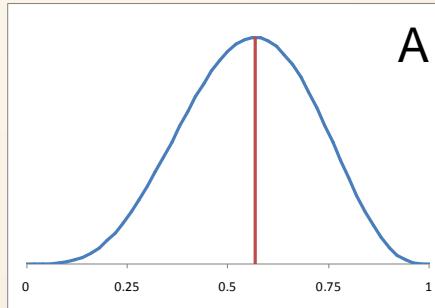
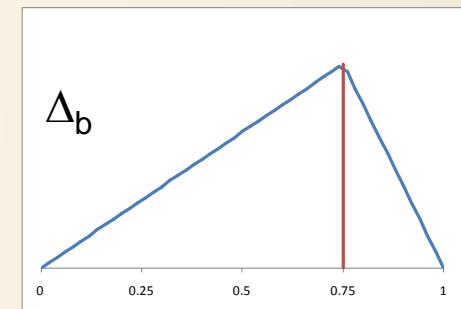
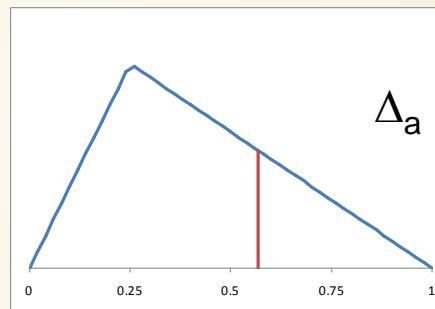
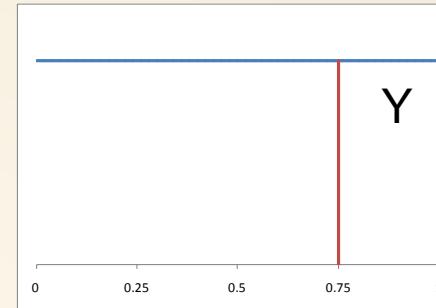
How does dependence materialize throughout this Bayesian Network?



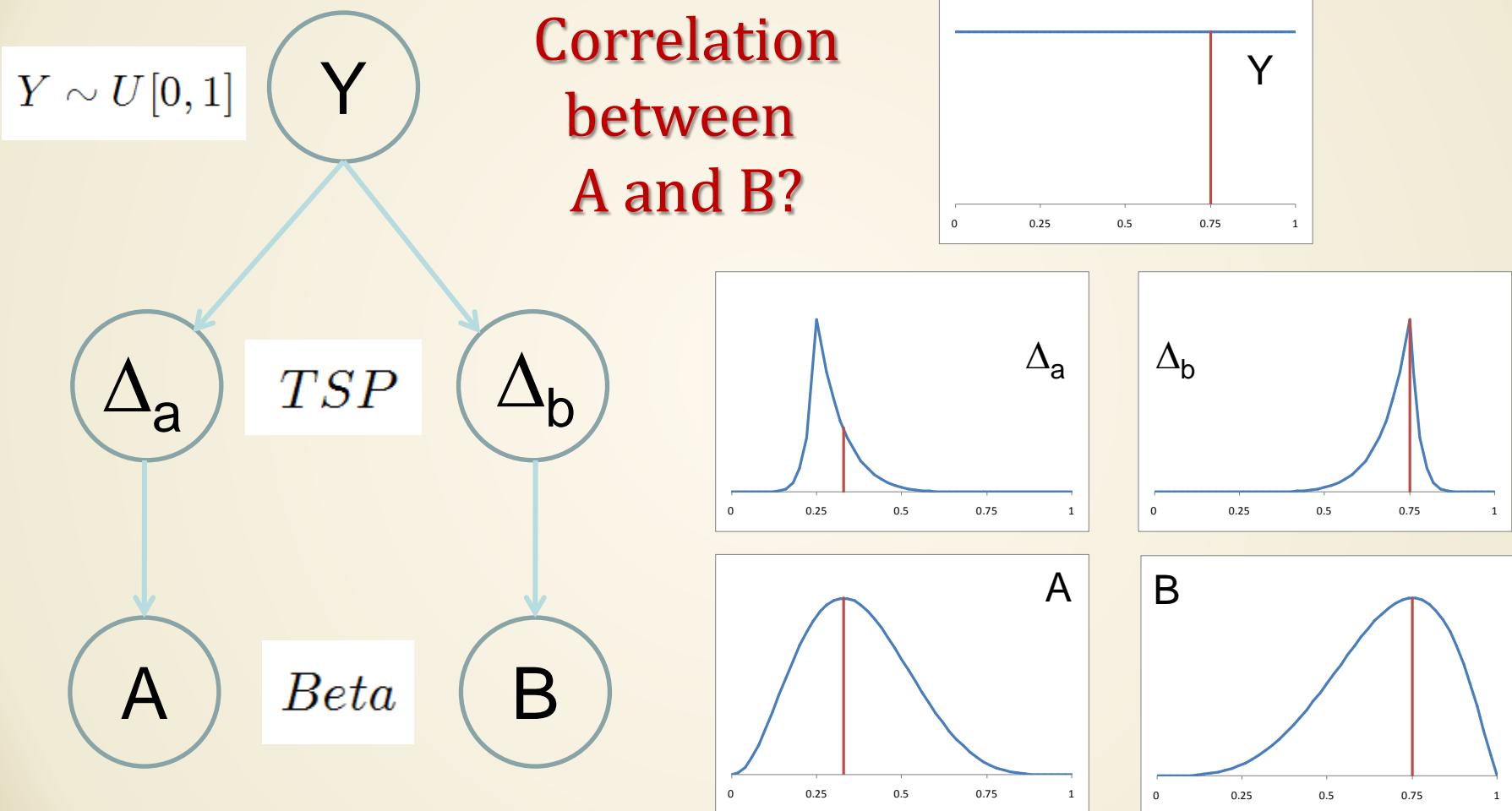
How does dependence materialize throughout this Bayesian Network?



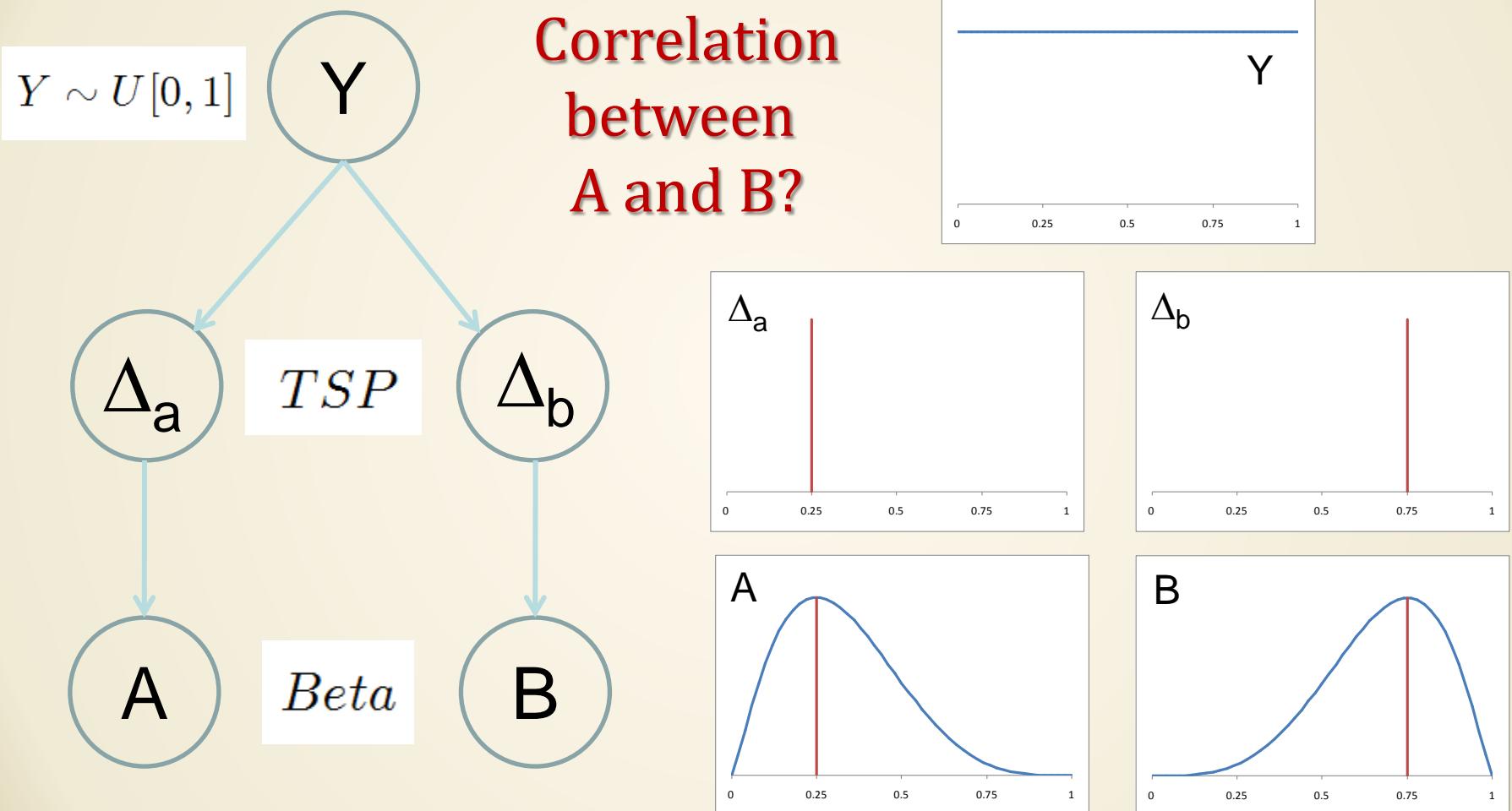
Correlation between A and B?



How does dependence materialize throughout the Bayesian Network?



How does dependence materialize throughout the Bayesian Network?



How does dependence materialize throughout the Bayesian Network?

Conclusion: Assuming Activities share a common *TSP* shape parameter n and a common *Beta* shape parameter γ we have:

- Keeping n constant **the correlation increases with increasing γ**
- Keeping γ constant **the correlation decreases with increasing n**

Assuming **common TSP shape parameter n** and **common Beta shape parameter γ** amongst activities, how does one specify them using expert elicitation **building on** Malcolm's et al. (1959) PERT method?

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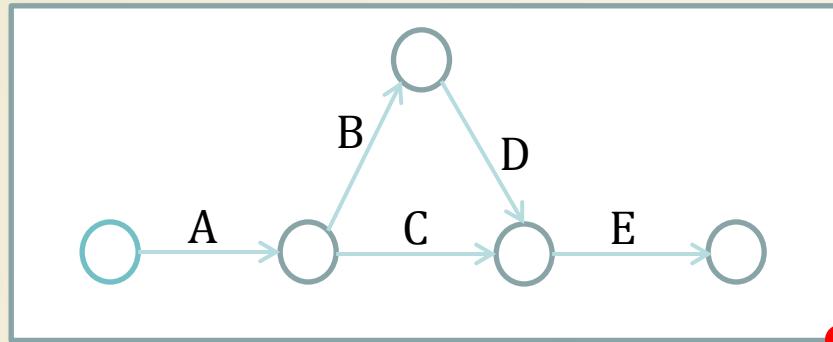
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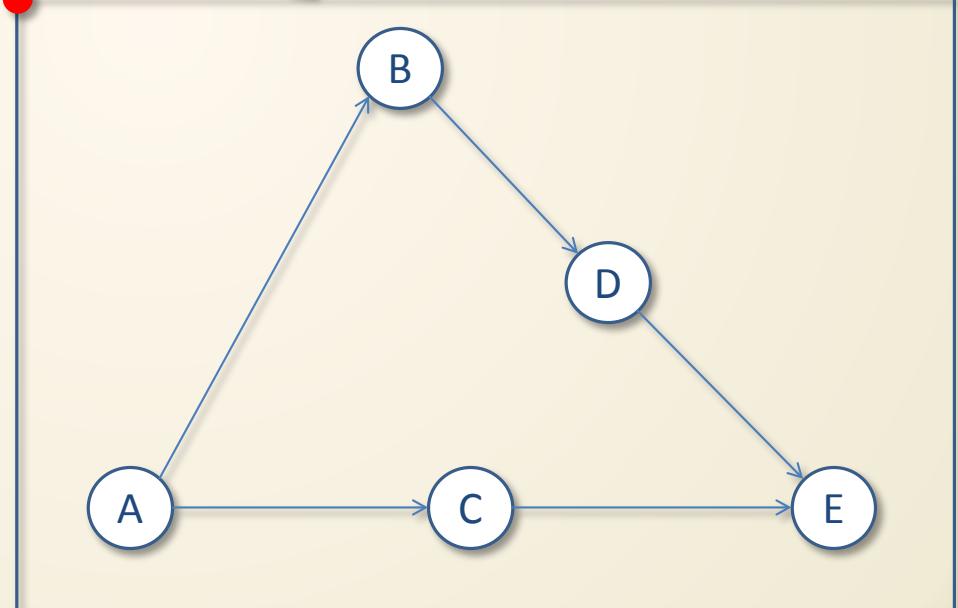
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Small Activity Network Example



Activity-on-Arc
Representation

Activity-on-Node
Representation



Eliciting Conditional Medians

“Suppose Activity A has finished above its median value $a_{0.5}$,
what is the probability that
Activity B finishes above its median value $b_{0.5}$? ”

If answer is “ = 0.50 ” , knowledge of A does not influence B

If answer is “ > 0.50 ” , knowledge of A does influence B

If answer is “ = 1.00 ” , knowledge of A influences B “the most”

Elicit activity conditional medians that are directly path-connected

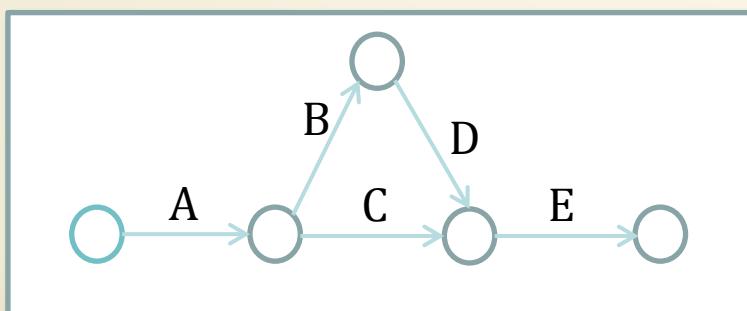
$$1. \Pr \{B > b_{0.5} | A > a_{0.5}\}$$

$$2. \Pr \{C > c_{0.5} | A > a_{0.5}\}$$

$$3. \Pr \{D > d_{0.5} | B > b_{0.5}\}$$

$$4. \Pr \{E > e_{0.5} | C > c_{0.5}\}$$

$$5. \Pr \{E > e_{0.5} | D > d_{0.5}\}$$



Conditional Median Matrix

Notation: $\Pr \{ Y > y_{0.5} | X > x_{0.5} \} = \text{Med}(Y|X)$

	A	B	C	D	E
A	1	$\text{Med}(B A)$	$\text{Med}(C A)$	$\text{Med}(D A)$	$\text{Med}(E A)$
B	$\text{Med}(A B)$	1	$\text{Med}(C B)$	$\text{Med}(D B)$	$\text{Med}(E B)$
C	$\text{Med}(A C)$	$\text{Med}(B C)$	1	$\text{Med}(D C)$	$\text{Med}(E C)$
D	$\text{Med}(A D)$	$\text{Med}(B D)$	$\text{Med}(C D)$	1	$\text{Med}(E D)$
E	$\text{Med}(A E)$	$\text{Med}(B E)$	$\text{Med}(C E)$	$\text{Med}(D E)$	1

Conditional Median Matrix is Symmetric:

$$\begin{aligned}
 \text{Med}(X|Y) &= \Pr \{ X > x_{0.5} | Y > y_{0.5} \} = \frac{\Pr \{ Y > y_{0.5} | X > x_{0.5} \} \Pr \{ X > x_{0.5} \}}{\Pr \{ Y > y_{0.5} \}} \\
 &= \frac{\Pr \{ Y > y_{0.5} | X > x_{0.5} \} \times 0.5}{0.5} = \Pr \{ Y > y_{0.5} | X > x_{0.5} \} = \text{Med}(Y|X) \quad 24
 \end{aligned}$$

Conditional Median Matrix

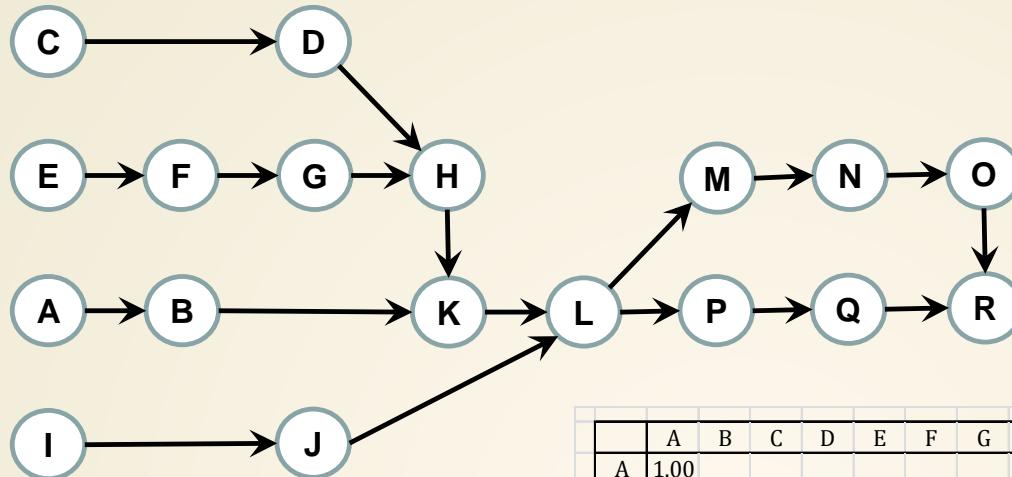
Notation: $\Pr \{ Y > \text{Med}(Y) \mid X > \text{Med}(X) \} = \text{Med}(Y|X)$

	A	B	C	D	E
A	1	$\text{Med}(B A)$	$\text{Med}(C A)$	$\text{Med}(D A)$	$\text{Med}(E A)$
B		1	$\text{Med}(C B)$	$\text{Med}(D B)$	$\text{Med}(E B)$
C			1	$\text{Med}(D C)$	$\text{Med}(E C)$
D				1	$\text{Med}(E D)$
E					1

Average Conditional Median

$$\overline{\text{Med}(\cdot | \cdot)} = \frac{\sum_{\substack{Y \in \{A, B, C, D, E\} \\ Y \neq X}} \sum_{X \in \{A, B, C, D, E\}} \text{Med}(Y | X)}{5 \times (5 - 1)}$$

Back to Case Study



Eliciting only activity-to-activity conditional medians that are directly connected in Project Network reduces elicitation burden here from:

$\binom{18}{2}$ to 18 conditional medians



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	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
A	1.00																	
B	0.65	1.00																
C			1.00															
D			0.65	1.00														
E					1.00													
F					0.70	1.00												
G						0.65	1.00											
H						0.70		0.60	1.00									
I									1.00									
J									0.70	1.00								
K				0.75						0.65		1.00						
L										0.65	0.60	1.00						
M											0.70	1.00						
N												0.55	1.00					
O												0.70	1.00					
P												0.65				1.00		
Q													0.65	1.00				
R													0.70		0.60	1.00		

Average Conditional Median ≈ 0.658

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Algorithmic Selection Procedure Parameters β and n:

1. For different values of β and n do:

- Sample 1000 joint activity samples from joint prior (defined by BN)
- Evaluate Average Prior Marginal Activity Variance
- Evaluate Average Prior Activity Statistical Dependence

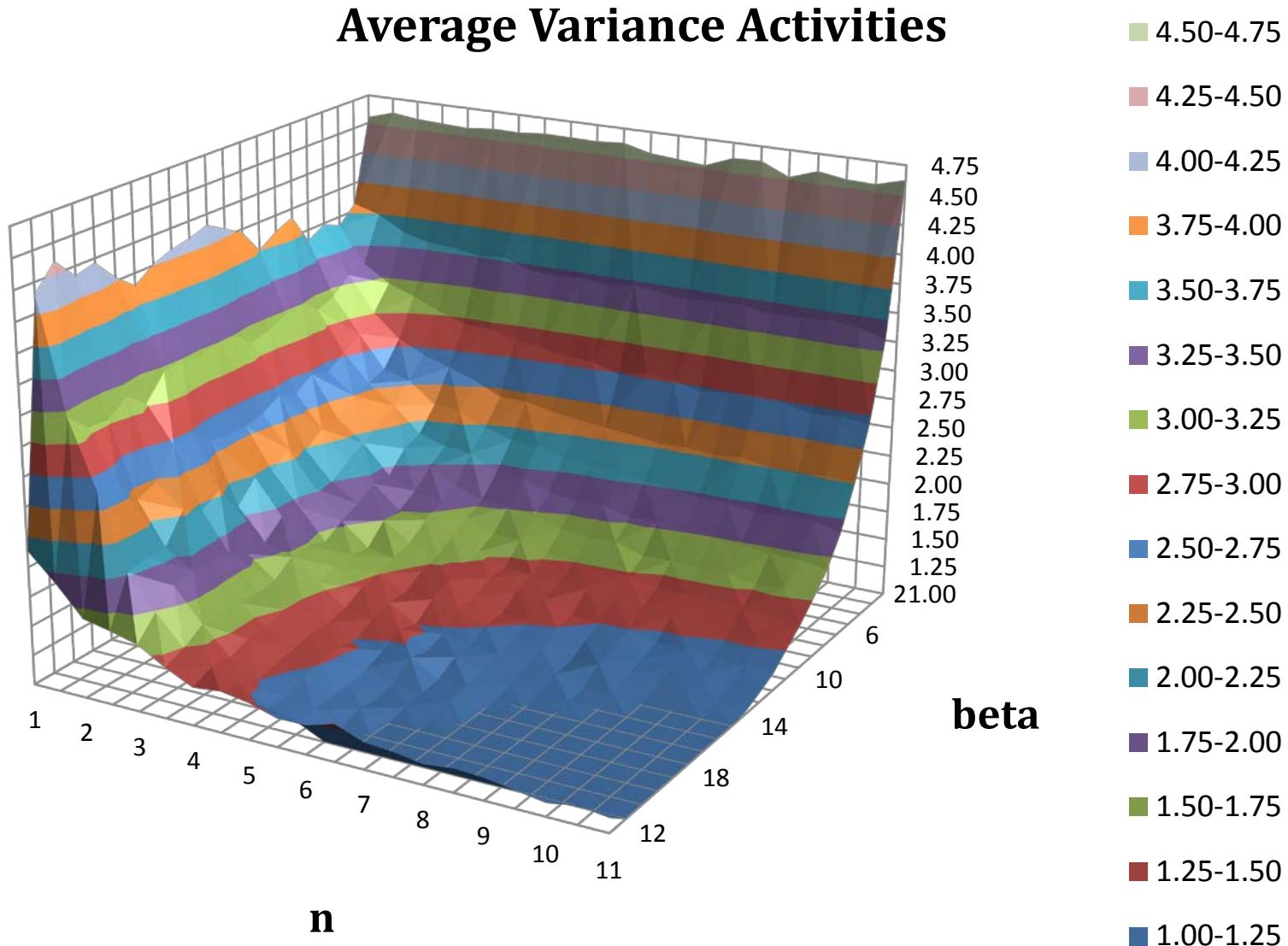
2. Select values of β and n such that:

- Average Prior Marginal Activity Variance close to Average Modified PERT Variance across Project Network
- Average Prior Activity to Activity Statistical Dependence close to Elicited Average Activity to Activity Statistical Dependence

3. For selected values of β and n do:

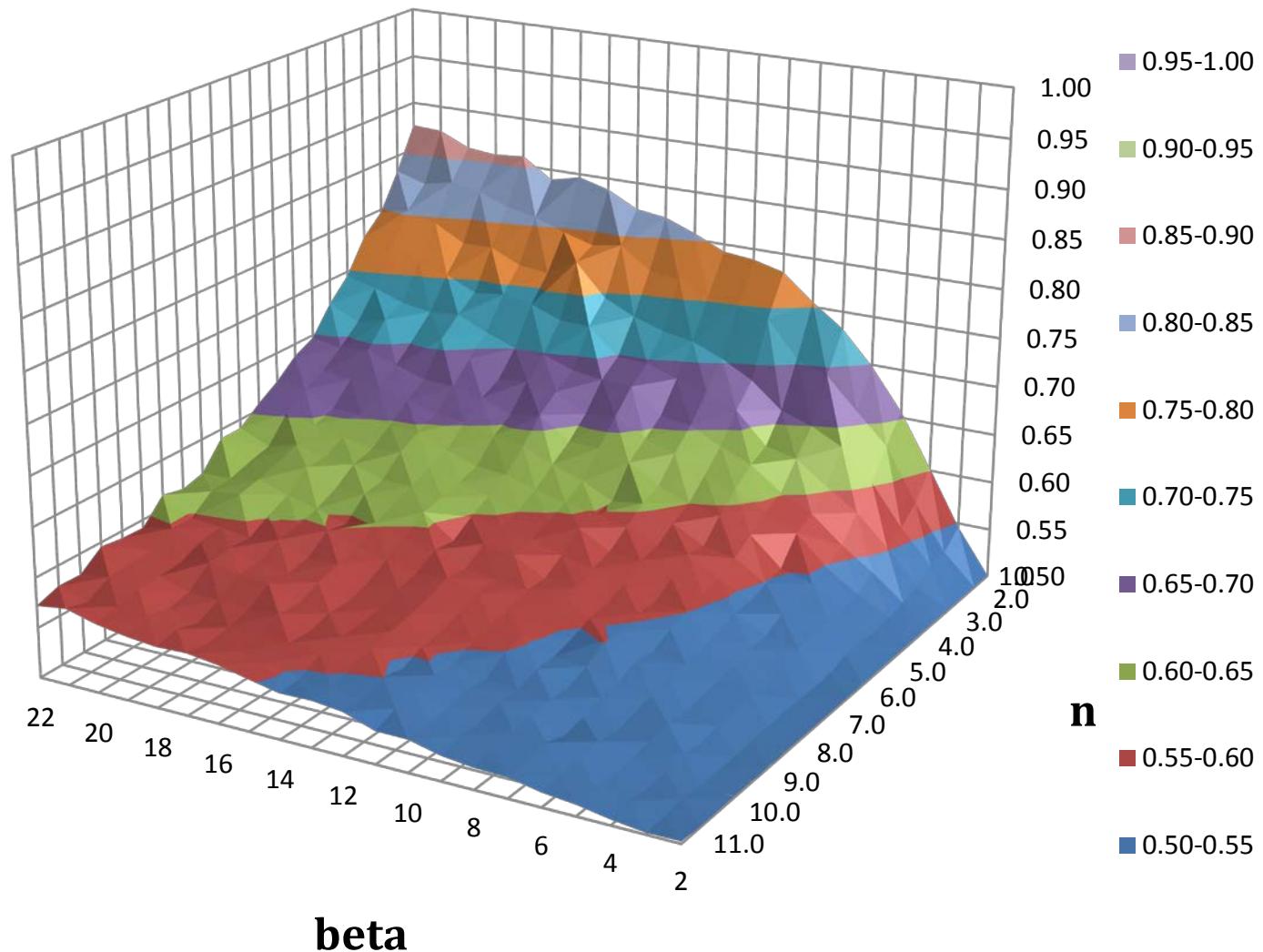
- a. Sample 1000 Joint activities from Bayesian Network Prior
- b. Evaluate Average Prior Marginal Activity Variance
- c. Evaluate Average Prior Activity Statistical Dependence
- d. Repeat Steps a, b and c one 1000 times and plot:
 - Average Prior Marginal Activity Variance Uncertainty
 - Average Prior Activity to Activity Statistical Dependence Uncertainty
- e. Test if Average Modified PERT Variance and Elicited Average Statistical dependence fall within 90% credibility limits of uncertainty distributions

STEP 1: Prior Average Variance (β , n)



STEP 1: Prior Average Activity Cond. Med(β , n)

Average Activity Conditional Median



STEP 2: Select values of β and n that are close

β

Prior Average Activity Variance between 1.50 and 2.00

n

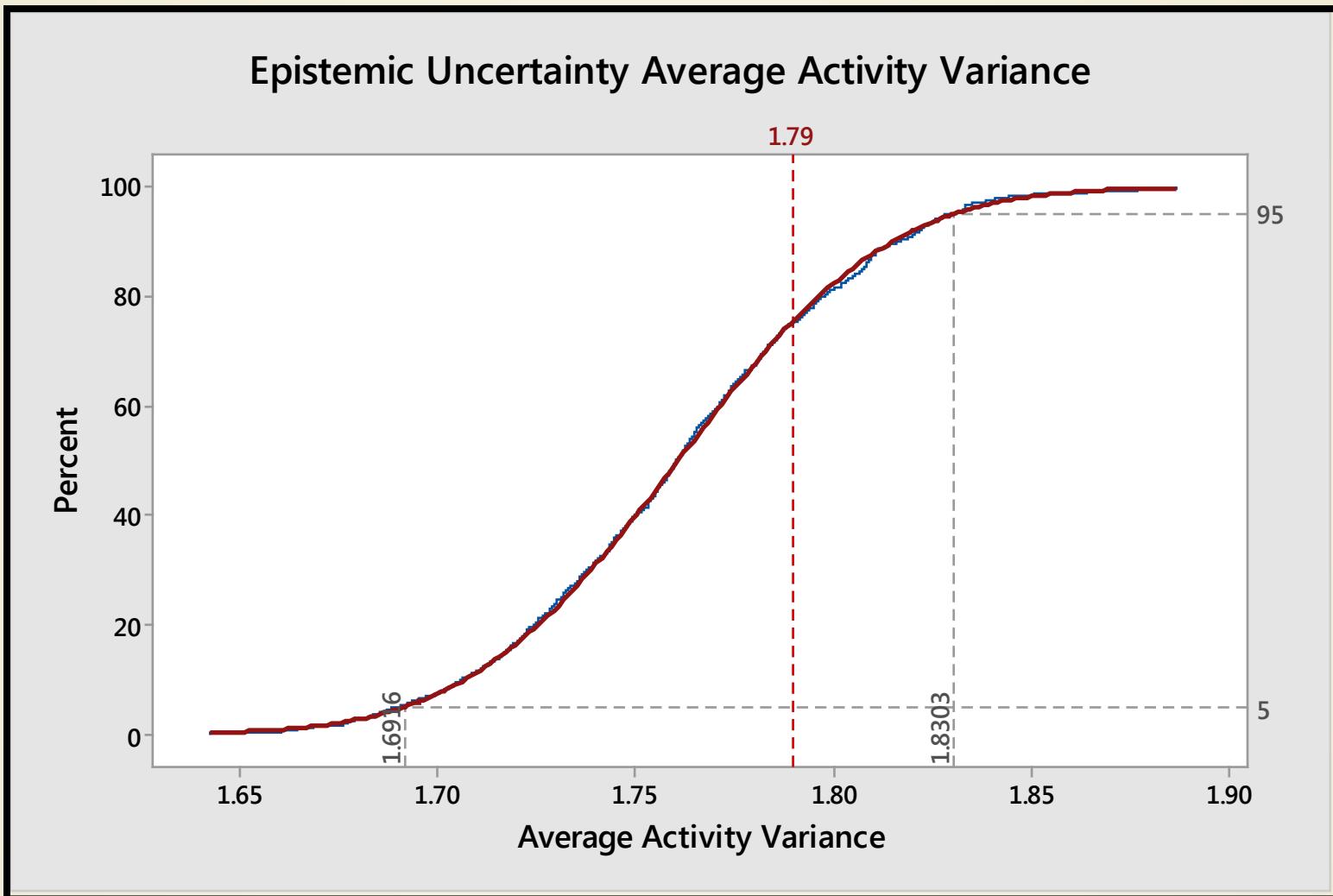
	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1.0	4.53	3.80	3.65	3.59	3.66	3.69	3.77	3.96	3.83	3.78	4.00	3.98	3.97	4.13	4.19	3.93	4.30	4.26	4.16	4.28	4.31
1.5	4.54	3.69	3.40	3.34	3.23	3.23	3.10	3.17	3.19	3.12	3.10	3.04	3.22	3.09	3.14	3.12	3.18	3.17	3.20	3.17	3.11
2.0	4.56	3.61	3.19	3.01	2.90	2.83	2.59	2.61	2.75	2.67	2.56	2.57	2.52	2.72	2.53	2.53	2.49	2.50	2.61	2.61	2.62
2.5	4.61	3.62	3.15	2.87	2.68	2.52	2.40	2.42	2.35	2.33	2.30	2.17	2.16	2.13	2.22	2.13	2.13	2.03	2.11	2.15	2.12
3.0	4.65	3.57	2.99	2.64	2.49	2.37	2.25	2.15	2.09	2.04	2.06	2.00	1.87	1.89	1.83	1.75	1.78	1.74	1.84	1.79	1.78
3.5	4.58	3.56	2.94	2.64	2.42	2.25	2.12	1.96	1.95	1.85	1.93	1.69	1.74	1.73	1.65	1.60	1.69	1.58	1.59	1.52	1.56
4.0	4.62	3.51	2.91	2.54	2.28	2.13	2.01	1.84	1.73	1.75	1.71	1.55	1.61	1.57	1.51	1.46	1.38	1.40	1.40	1.35	1.35
4.5	4.57	3.48	2.88	2.46	2.19	2.07	1.89	1.75	1.73	1.53	1.56	1.49	1.48	1.45	1.39	1.35	1.35	1.31	1.27	1.23	1.25
5.0	4.54	3.46	2.86	2.49	2.15	2.00	1.84	1.68	1.64	1.56	1.44	1.36	1.35	1.30	1.27	1.28	1.22	1.21	1.10	1.14	1.14
5.5	4.62	3.44	2.82	2.43	2.13	1.91	1.78	1.69	1.53	1.47	1.37	1.33	1.31	1.24	1.21	1.18	1.11	1.12	1.11	1.07	1.06
6.0	4.60	3.46	2.83	2.39	2.08	1.90	1.67	1.61	1.48	1.41	1.34	1.27	1.23	1.21	1.14	1.10	1.09	1.05	1.02	0.99	1.00
6.5	4.55	3.37	2.80	2.27	2.07	1.88	1.70	1.56	1.46	1.35	1.31	1.23	1.16	1.18	1.11	1.08	1.04	1.07	0.96	0.91	0.98
7.0	4.61	3.41	2.75	2.35	2.05	1.87	1.67	1.52	1.40	1.35	1.23	1.20	1.17	1.09	1.09	1.01	0.99	0.99	0.97	0.89	0.88
7.5	4.54	3.41	2.78	2.31	2.01	1.77	1.67	1.48	1.40	1.30	1.22	1.19	1.12	1.04	1.03	1.00	0.96	0.91	0.92	0.89	0.85
8.0	4.55	3.46	2.74	2.30	2.01	1.77	1.62	1.45	1.39	1.26	1.20	1.12	1.08	1.01	1.00	0.93	0.94	0.87	0.85	0.84	0.83
8.5	4.58	3.41	2.69	2.30	1.95	1.73	1.59	1.45	1.35	1.24	1.14	1.13	1.05	1.01	0.94	0.91	0.89	0.86	0.82	0.80	0.77
9.0	4.57	3.38	2.79	2.30	1.95	1.74	1.57	1.42	1.28	1.21	1.16	1.10	1.00	0.97	0.94	0.93	0.87	0.85	0.80	0.77	0.76
9.5	4.63	3.39	2.73	2.29	1.91	1.70	1.55	1.40	1.31	1.24	1.14	1.06	1.02	0.96	0.93	0.85	0.83	0.78	0.78	0.80	0.78
10.0	4.55	3.43	2.71	2.27	1.95	1.71	1.53	1.42	1.29	1.19	1.13	1.03	1.01	0.95	0.89	0.85	0.82	0.77	0.77	0.76	0.73
10.5	4.59	3.37	2.73	2.24	1.95	1.70	1.51	1.36	1.26	1.17	1.09	1.01	0.94	0.91	0.89	0.85	0.81	0.79	0.76	0.72	0.69
11.0	4.63	3.45	2.67	2.24	1.96	1.68	1.53	1.36	1.28	1.16	1.10	1.02	0.96	0.93	0.88	0.85	0.79	0.75	0.76	0.73	0.69

Prior Average Conditional Median between 0.625 and 0.675

	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1.0	0.50	0.55	0.60	0.66	0.70	0.73	0.75	0.78	0.79	0.79	0.81	0.82	0.82	0.84	0.85	0.84	0.86	0.86	0.86	0.87	0.88
1.5	0.50	0.53	0.58	0.63	0.66	0.69	0.71	0.74	0.75	0.75	0.77	0.77	0.79	0.79	0.80	0.81	0.83	0.83	0.82	0.83	0.83
2.0	0.50	0.53	0.56	0.60	0.63	0.65	0.66	0.69	0.70	0.72	0.72	0.73	0.75	0.78	0.76	0.77	0.78	0.78	0.80	0.80	0.80
2.5	0.50	0.52	0.55	0.58	0.60	0.63	0.63	0.66	0.68	0.69	0.70	0.70	0.72	0.73	0.74	0.74	0.75	0.76	0.77	0.78	0.78
3.0	0.50	0.51	0.54	0.56	0.59	0.60	0.62	0.64	0.65	0.66	0.68	0.68	0.69	0.70	0.70	0.71	0.73	0.72	0.73	0.74	0.75
3.5	0.50	0.51	0.53	0.55	0.58	0.59	0.61	0.62	0.63	0.64	0.66	0.66	0.68	0.68	0.68	0.69	0.71	0.70	0.72	0.71	0.73
4.0	0.50	0.51	0.52	0.54	0.55	0.58	0.59	0.60	0.61	0.63	0.64	0.64	0.66	0.66	0.67	0.67	0.68	0.69	0.70	0.69	0.70
4.5	0.50	0.51	0.52	0.54	0.55	0.57	0.57	0.59	0.61	0.60	0.62	0.63	0.64	0.64	0.65	0.66	0.67	0.67	0.68	0.69	0.69
5.0	0.50	0.51	0.52	0.54	0.54	0.56	0.58	0.58	0.59	0.60	0.60	0.61	0.62	0.62	0.63	0.65	0.65	0.65	0.67	0.67	0.67
5.5	0.50	0.50	0.52	0.53	0.54	0.55	0.56	0.58	0.58	0.58	0.60	0.60	0.61	0.61	0.62	0.63	0.64	0.63	0.64	0.65	0.66
6.0	0.50	0.50	0.52	0.53	0.54	0.55	0.55	0.56	0.57	0.58	0.59	0.59	0.60	0.61	0.62	0.62	0.63	0.63	0.64	0.63	0.64
6.5	0.50	0.50	0.51	0.52	0.53	0.54	0.55	0.56	0.57	0.57	0.58	0.59	0.59	0.61	0.61	0.61	0.61	0.61	0.62	0.62	0.64
7.0	0.50	0.50	0.52	0.52	0.53	0.53	0.55	0.55	0.56	0.57	0.57	0.58	0.58	0.59	0.59	0.59	0.60	0.59	0.61	0.62	0.61
7.5	0.50	0.50	0.51	0.52	0.53	0.54	0.55	0.55	0.55	0.56	0.57	0.58	0.58	0.58	0.59	0.60	0.60	0.60	0.62	0.61	0.61
8.0	0.50	0.50	0.51	0.52	0.52	0.53	0.54	0.54	0.55	0.56	0.56	0.57	0.57	0.57	0.58	0.58	0.59	0.59	0.60	0.61	0.61
8.5	0.50	0.50	0.51	0.52	0.52	0.53	0.53	0.54	0.54	0.55	0.55	0.56	0.57	0.57	0.58	0.58	0.58	0.59	0.59	0.60	0.59
9.0	0.50	0.50	0.51	0.51	0.52	0.52	0.52	0.53	0.53	0.53	0.54	0.54	0.55	0.56	0.57	0.57	0.58	0.58	0.59	0.59	0.59
9.5	0.50	0.50	0.51	0.51	0.52	0.52	0.53	0.54	0.54	0.54	0.55	0.56	0.56	0.56	0.57	0.57	0.57	0.57	0.58	0.58	0.60
10.0	0.50	0.50	0.51	0.51	0.52	0.52	0.53	0.53	0.53	0.54	0.55	0.55	0.56	0.56	0.56	0.56	0.57	0.57	0.57	0.57	0.58
10.5	0.50	0.50	0.51	0.51	0.52	0.52	0.53	0.53	0.53	0.54	0.54	0.54	0.55	0.55	0.56	0.56	0.57	0.57	0.57	0.57	0.58
11.0	0.50	0.50	0.51	0.51	0.52	0.52	0.52	0.52	0.53	0.53	0.54	0.55	0.55	0.55	0.56	0.56	0.56	0.56	0.57	0.57	0.57

Set $n = 3.5$ and $\beta = 13$

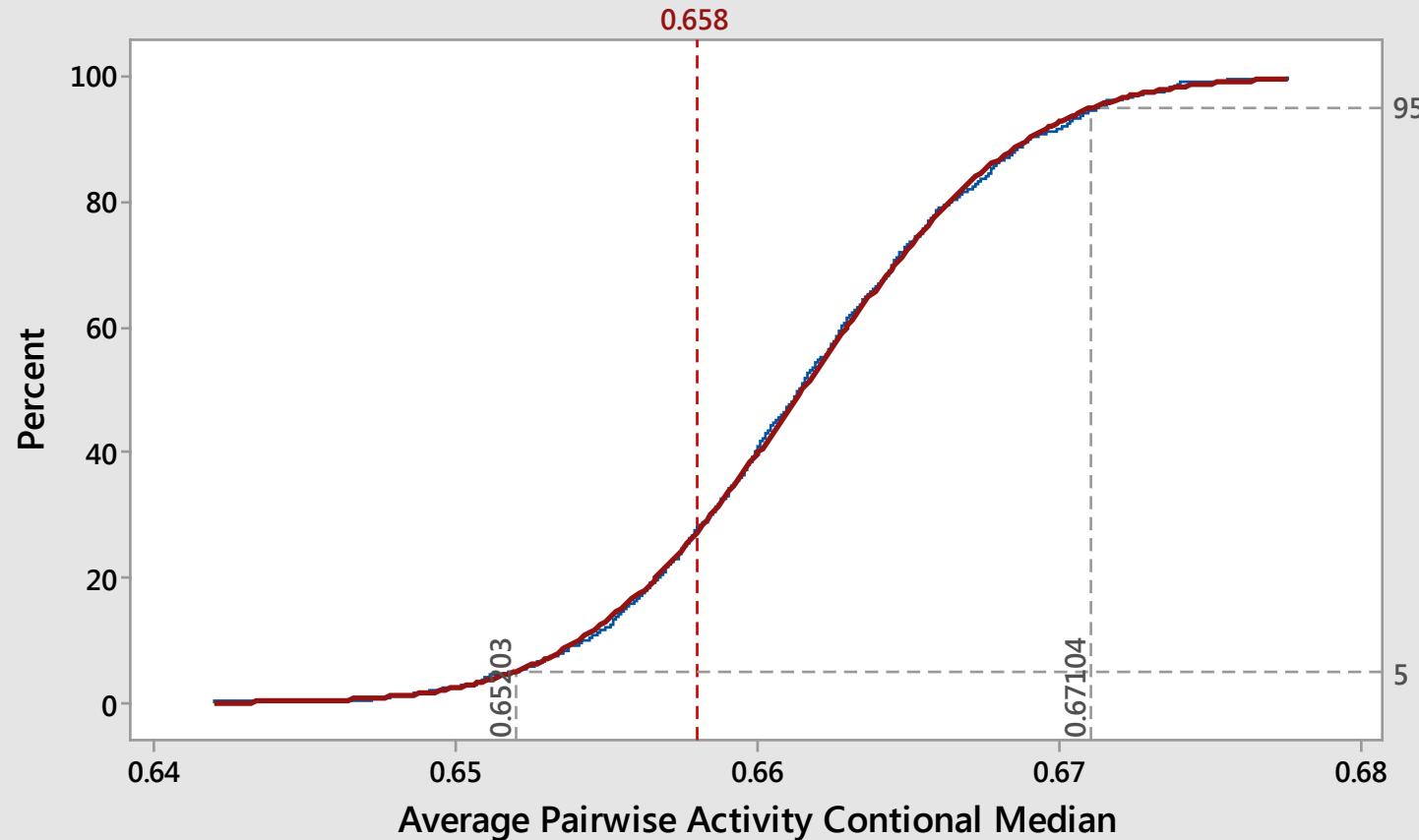
STEP 3: Evaluate Uncertainty given selected β and n



Setting $n = 3.5$ and $\beta = 13$

STEP 3: Evaluate Uncertainty given selected β and n

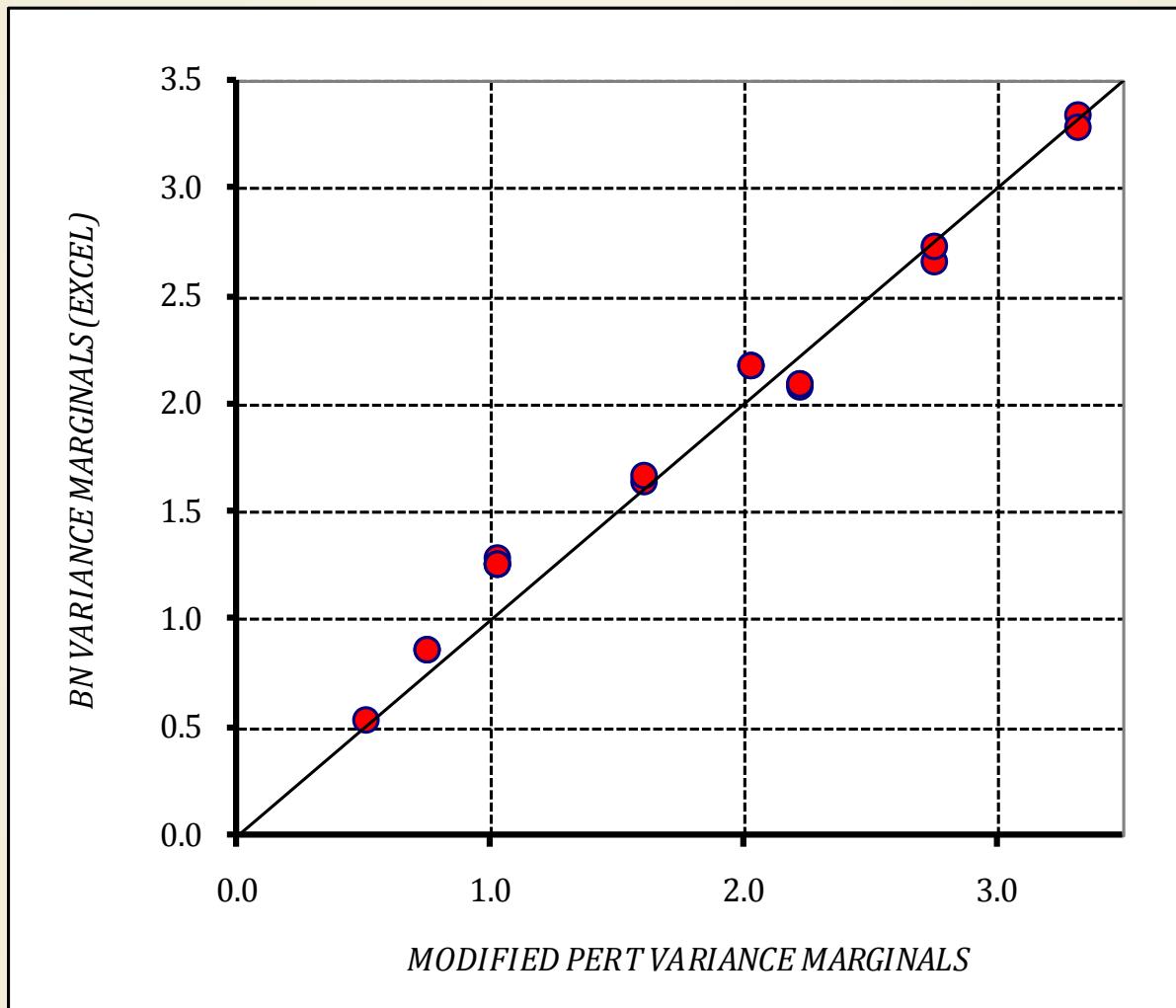
Epistemic Uncertainty Average Pairwise Activity Conditional Median



Setting $n = 3.5$ and $\beta = 13$

Additional Feedback for selected values of β and n

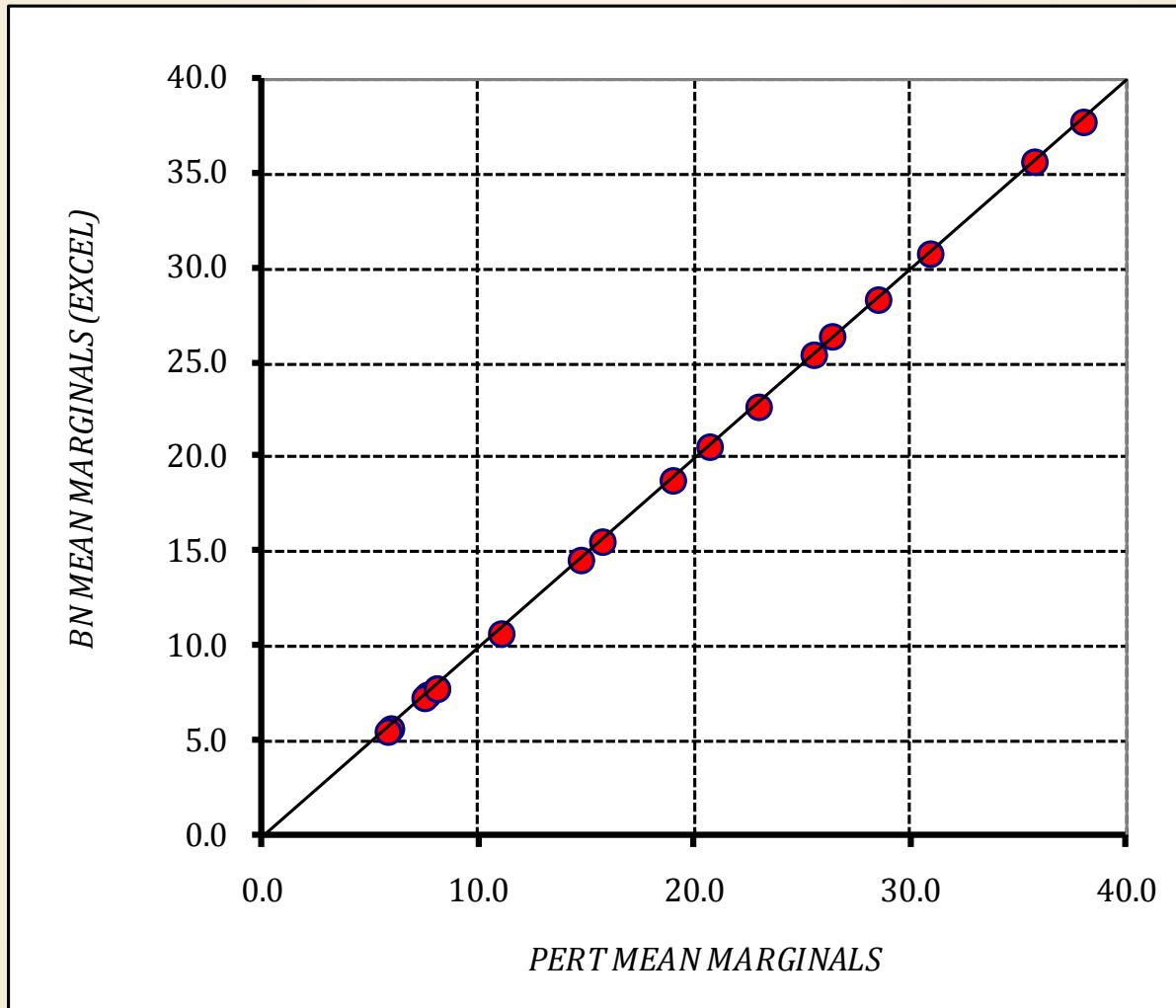
Setting n = 3.5 and $\beta = 13$



Activity Variances are close to Modified PERT Variances

Additional Feedback for selected values of β and n

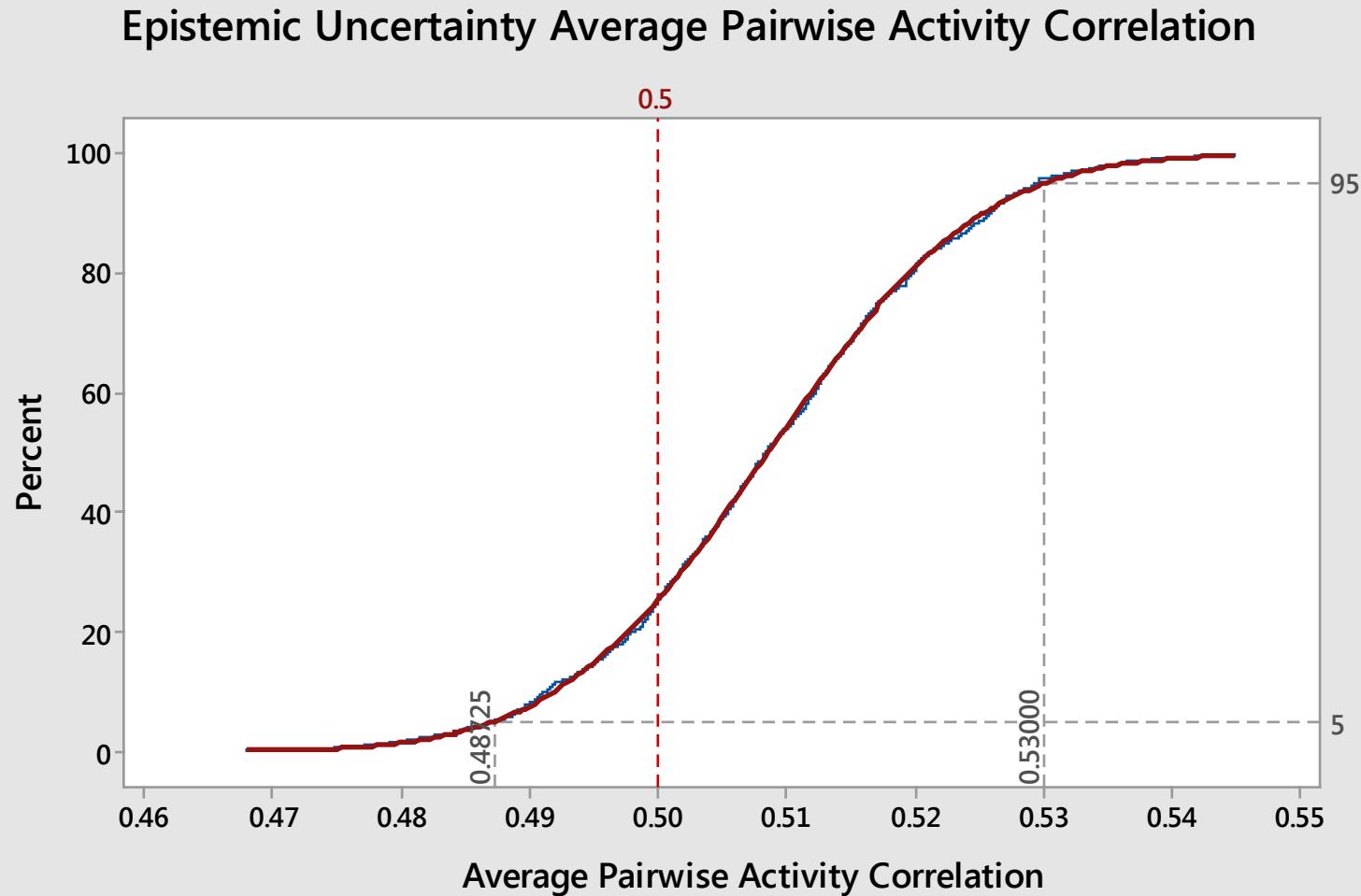
Setting n = 3.5 and β = 13



Activity Means are close to PERT Means

Additional Feedback for selected values of β and n

Setting n = 3.5 and $\beta = 13$



Average Pairwise Activity Correlation is close to 0.5

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- Case Study Description
- Bayesian Network Model
- Statistical Dependence Elicitation
- Uncertainty (n) and Dependence (β) Parameter Selection
- Prior Completion Time Uncertainty
- Posterior Analysis: Monitoring Uncertainty
- Conclusion

Johan Rene van Dorp
and Ifechukwu Nduka

SAN FRANCISCO 2014
INFORMS ANNUAL MEETING
BRIDGING DATA AND DECISIONS



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AND APPLIED SCIENCE

Cumulative Probability

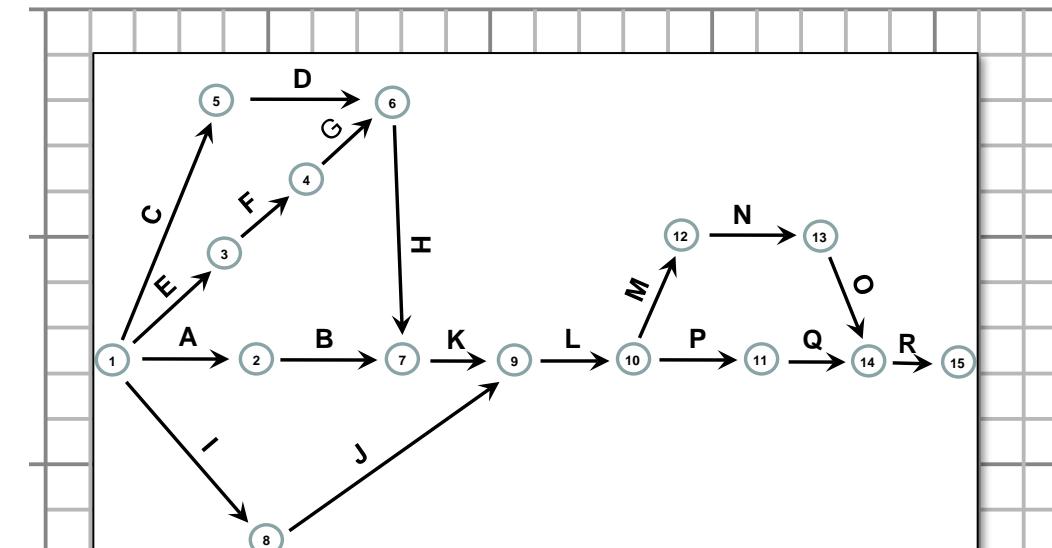
40%

30%

20%

10%

0%



Prior Project Completion Time Uncertainty

Comparing effect of
Statistical Independence
against
Statistical Dependence
on Prior Project Completion Time Distribution

125 135 145 155 165 175 185 195

150.8

152.2

CRITICAL PATH: E F G H K L P Q R

Project Completion Time

DEP P

IND P

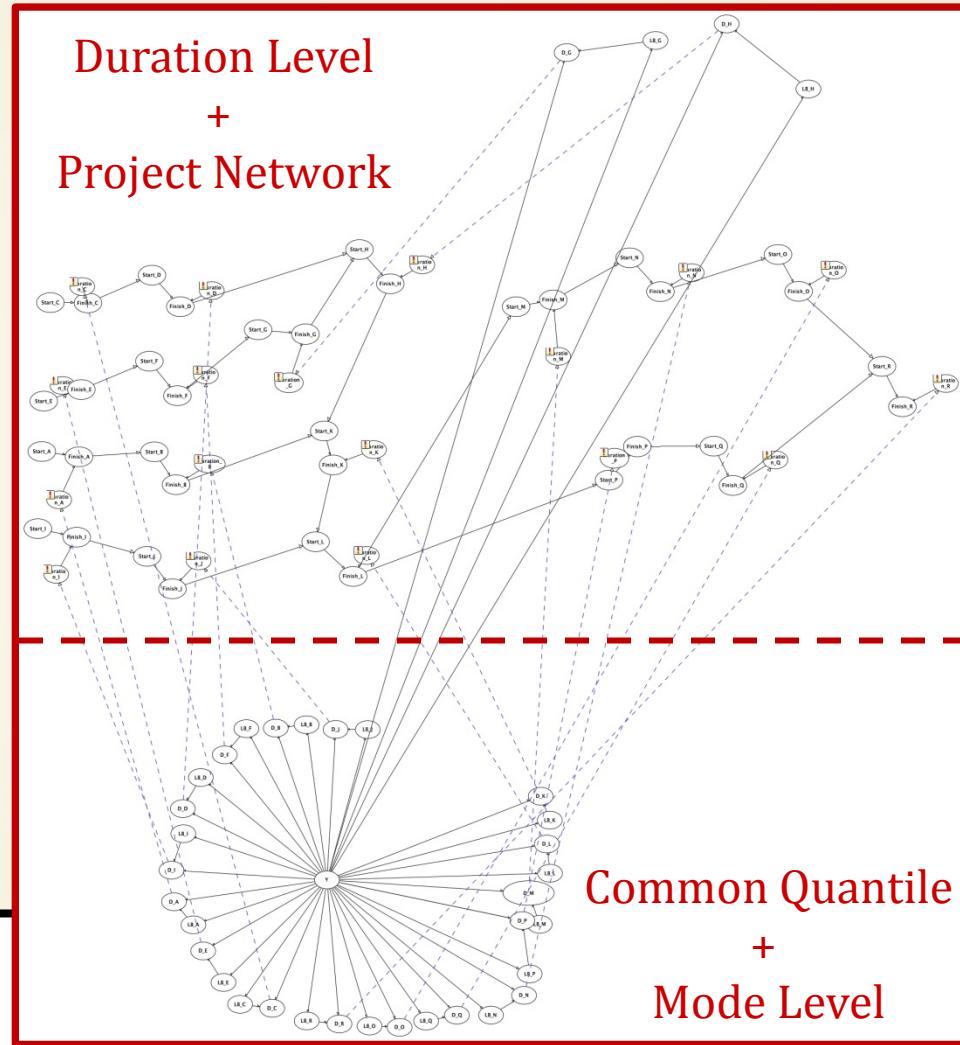
Bayesian Network Dependence Model for Project Risk Analysis (BNDM_PRA)

Project and
Bayes Network
Representation

in Software
Agena Risk

Posterior Analysis
performed in Software:

agena
Bayesian Network and Simulation Software for Risk Analysis and Decision Support



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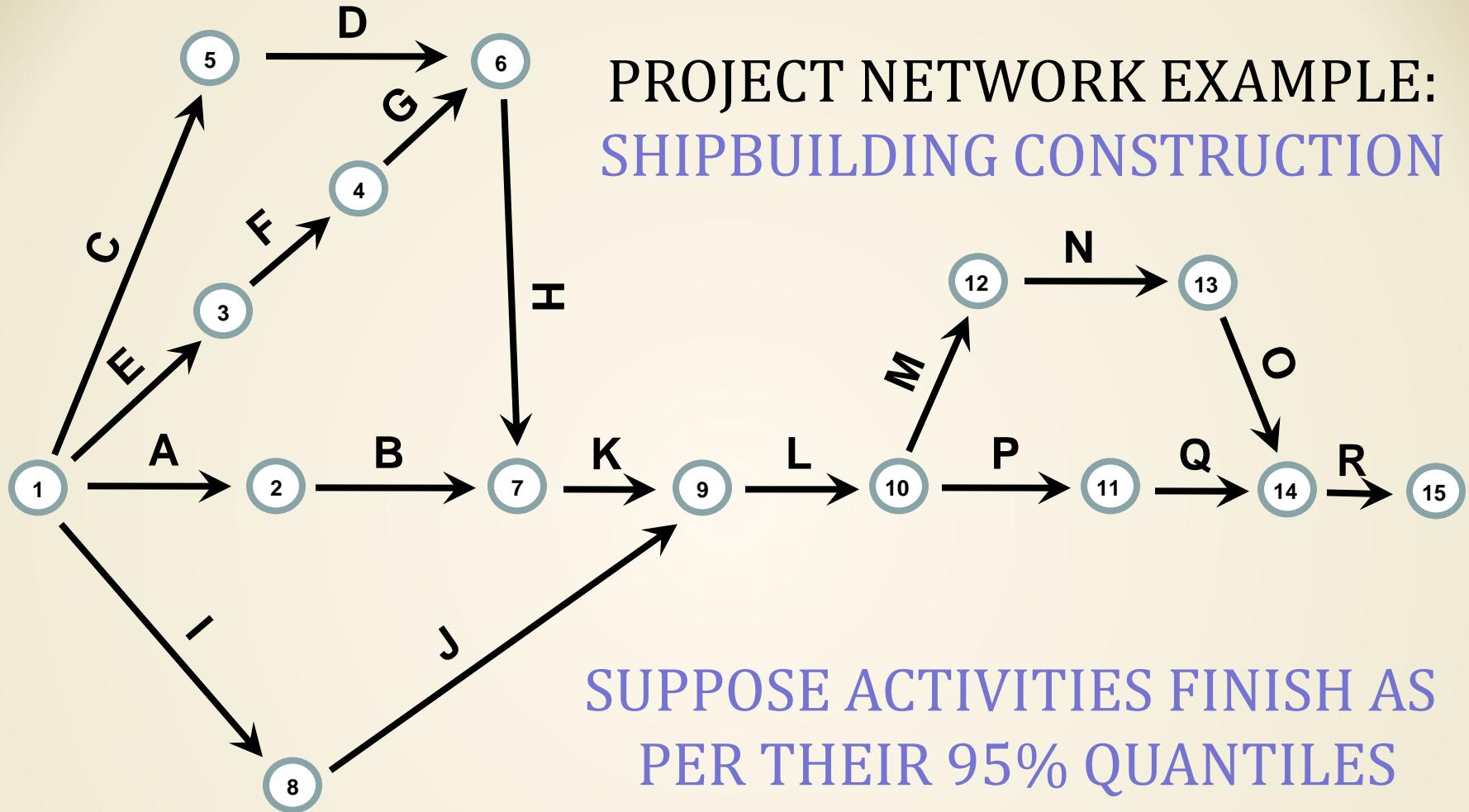
Johan Rene van Dorp
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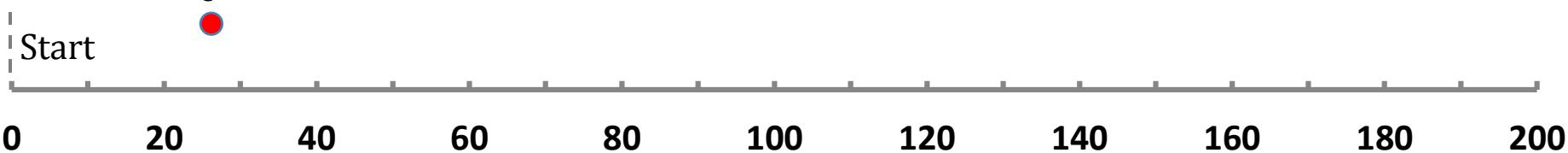
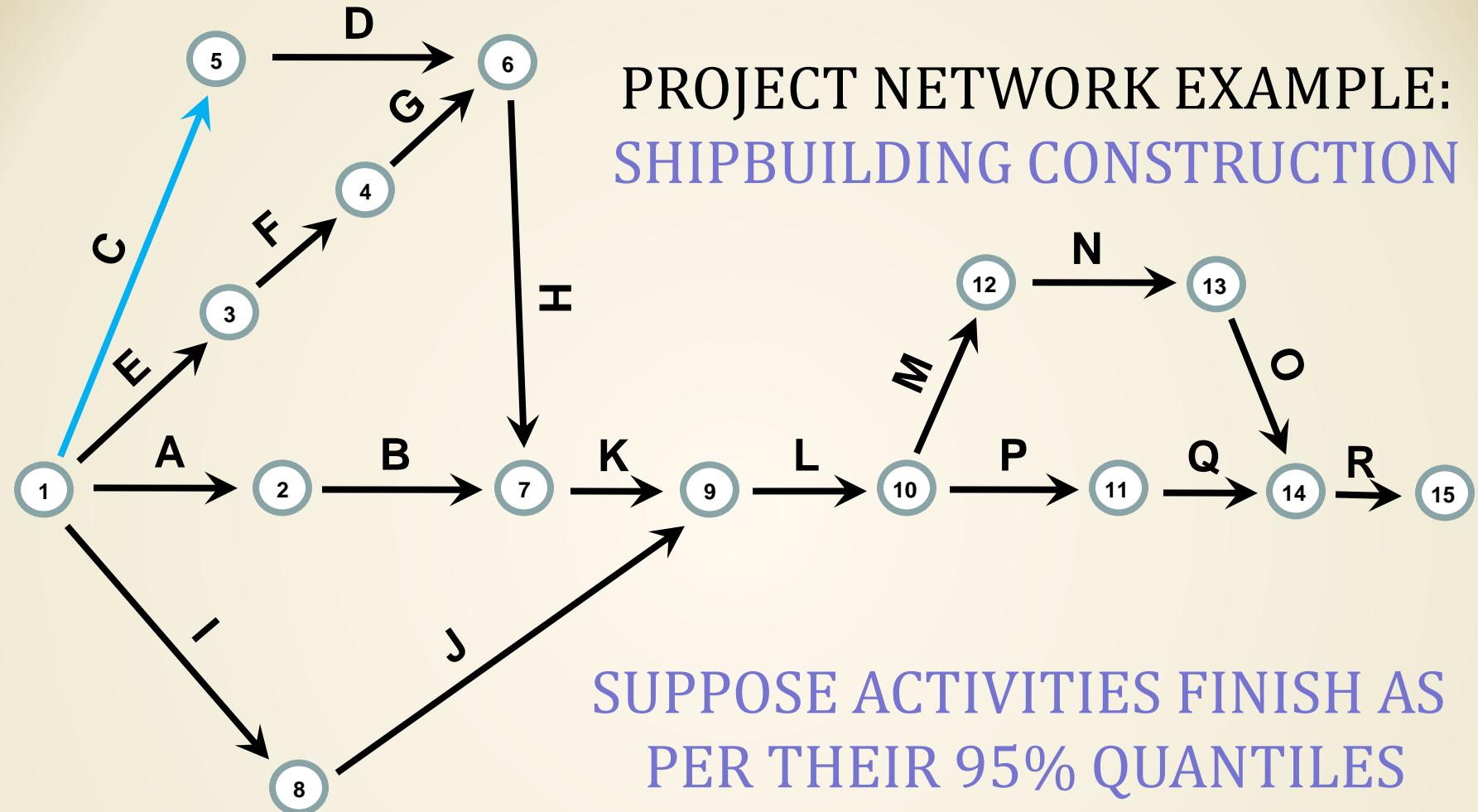
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



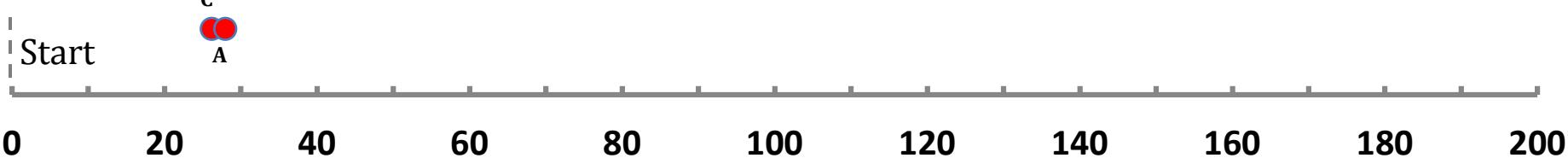
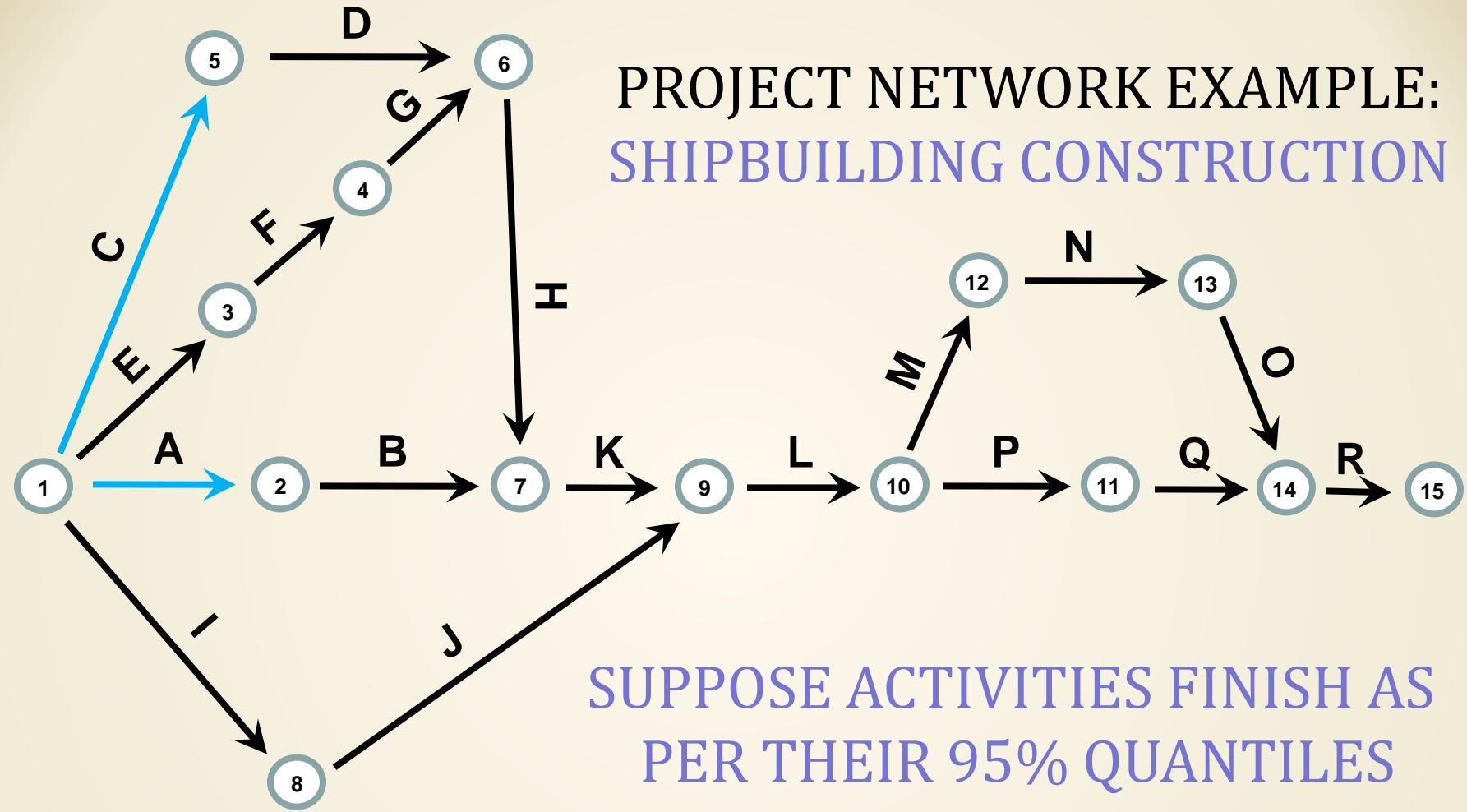
Start

0 20 40 60 80 100 120 140 160 180 200

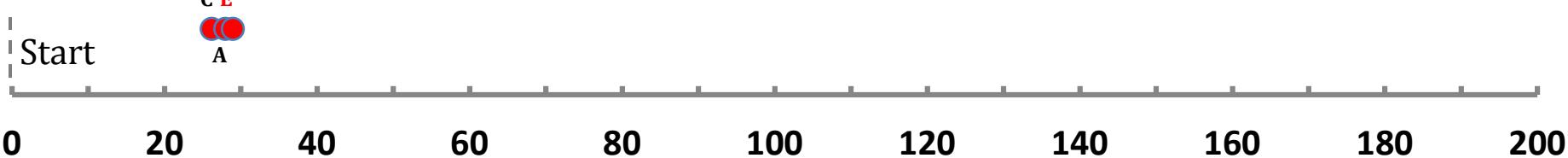
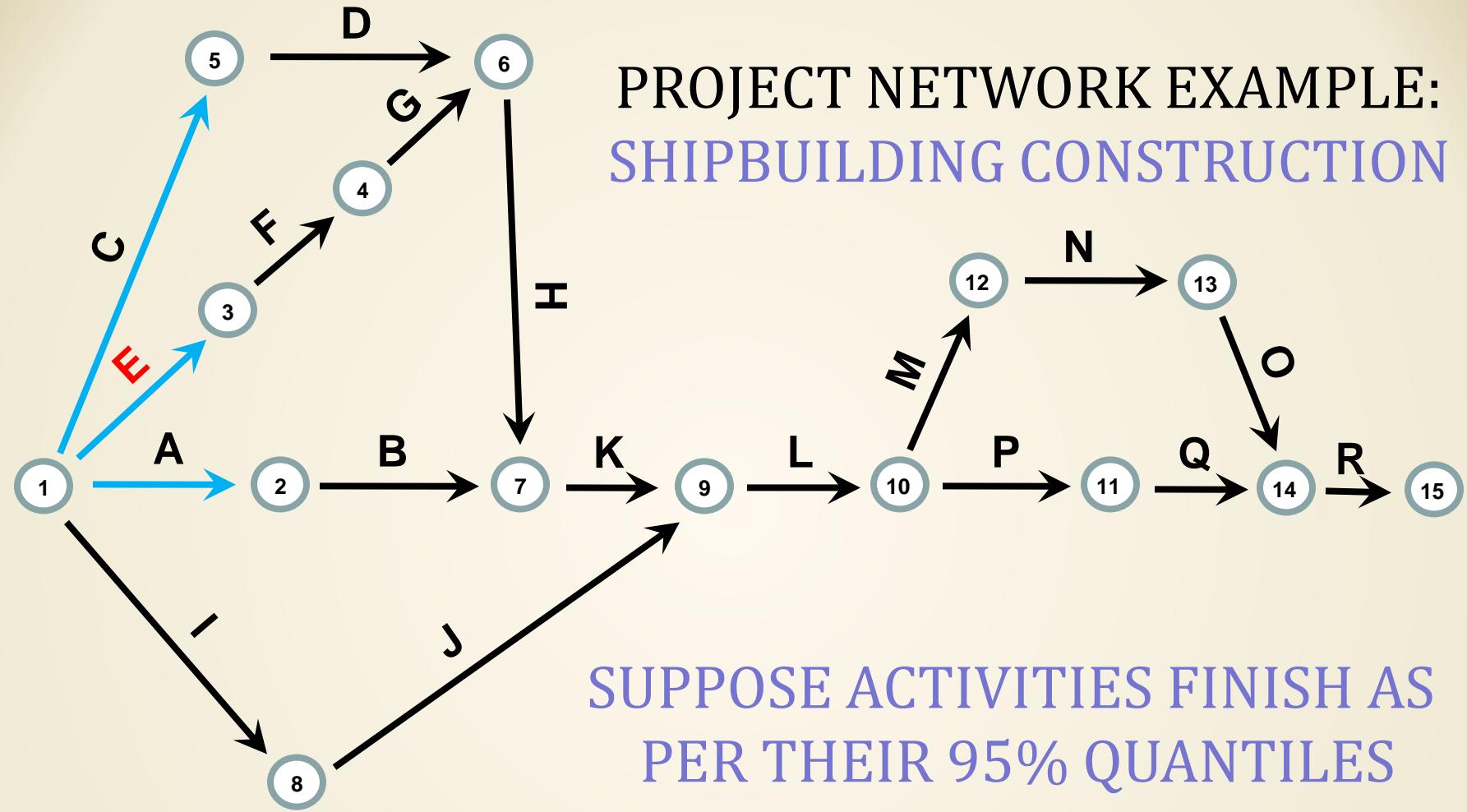
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



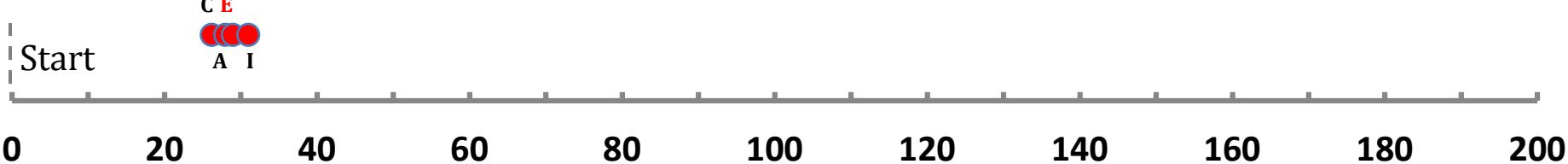
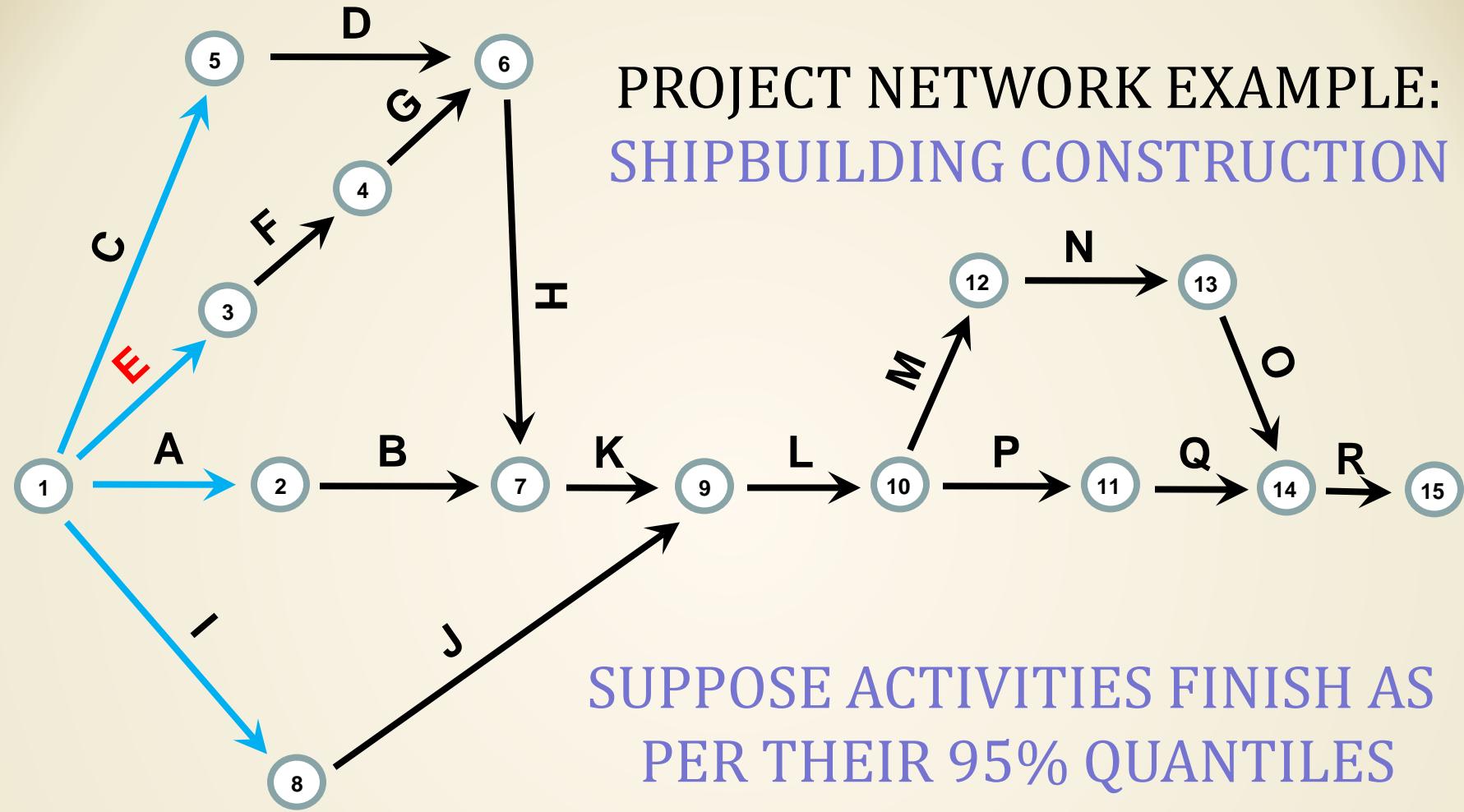
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



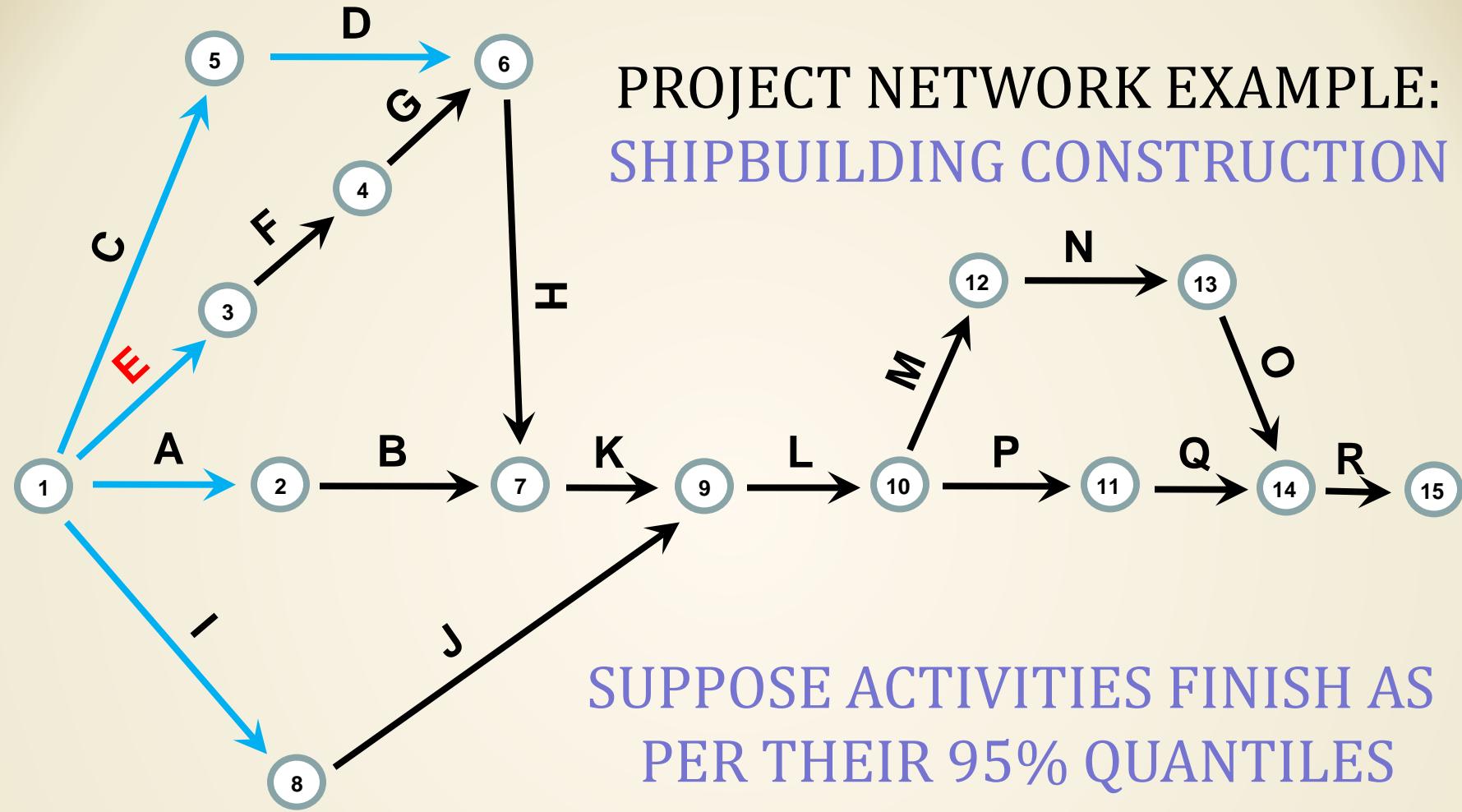
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION

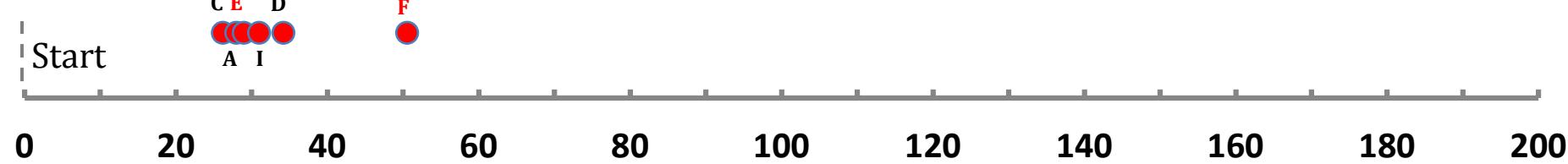
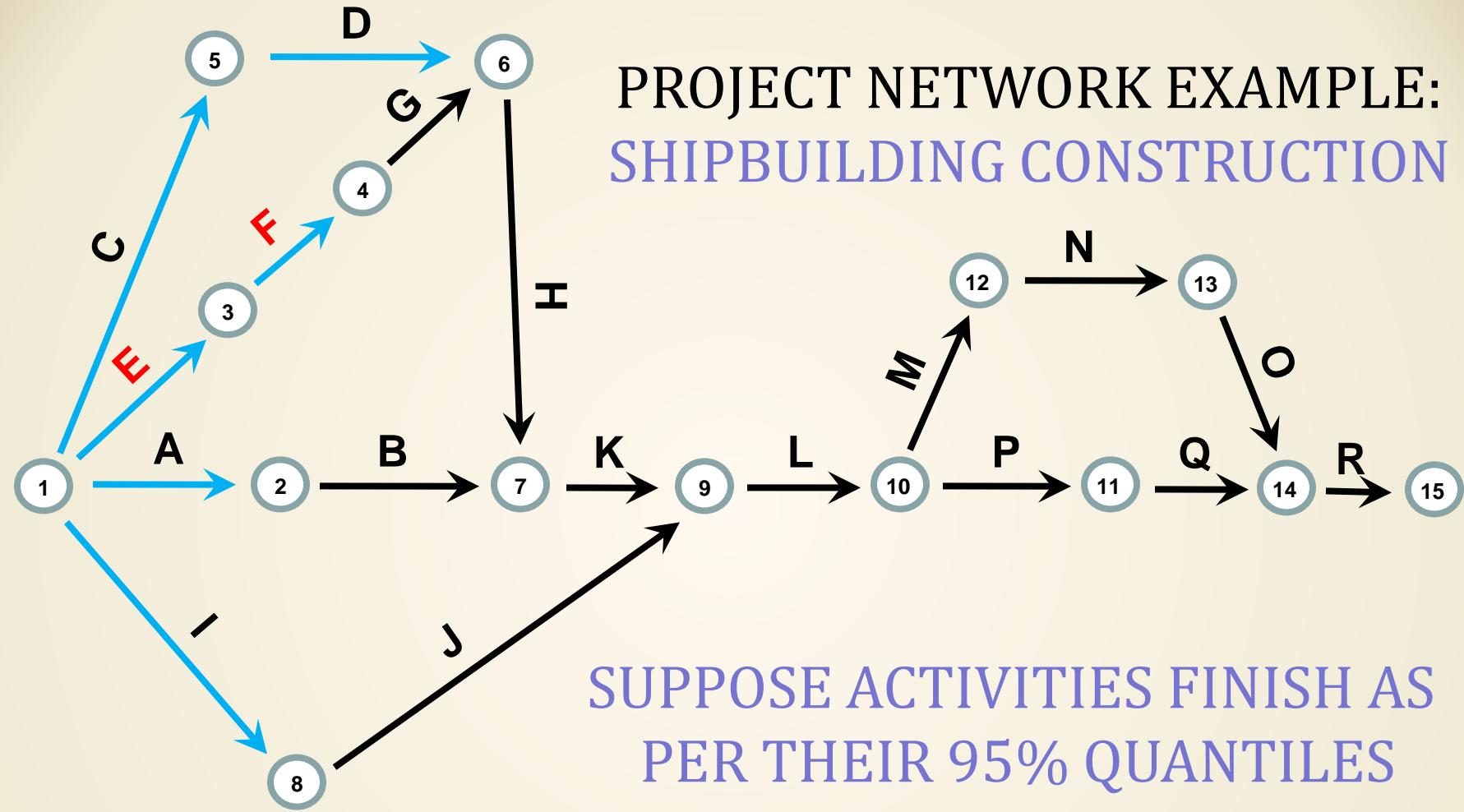


C E D
A I

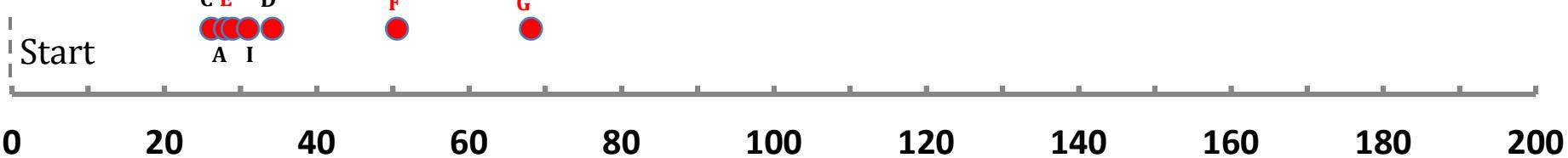
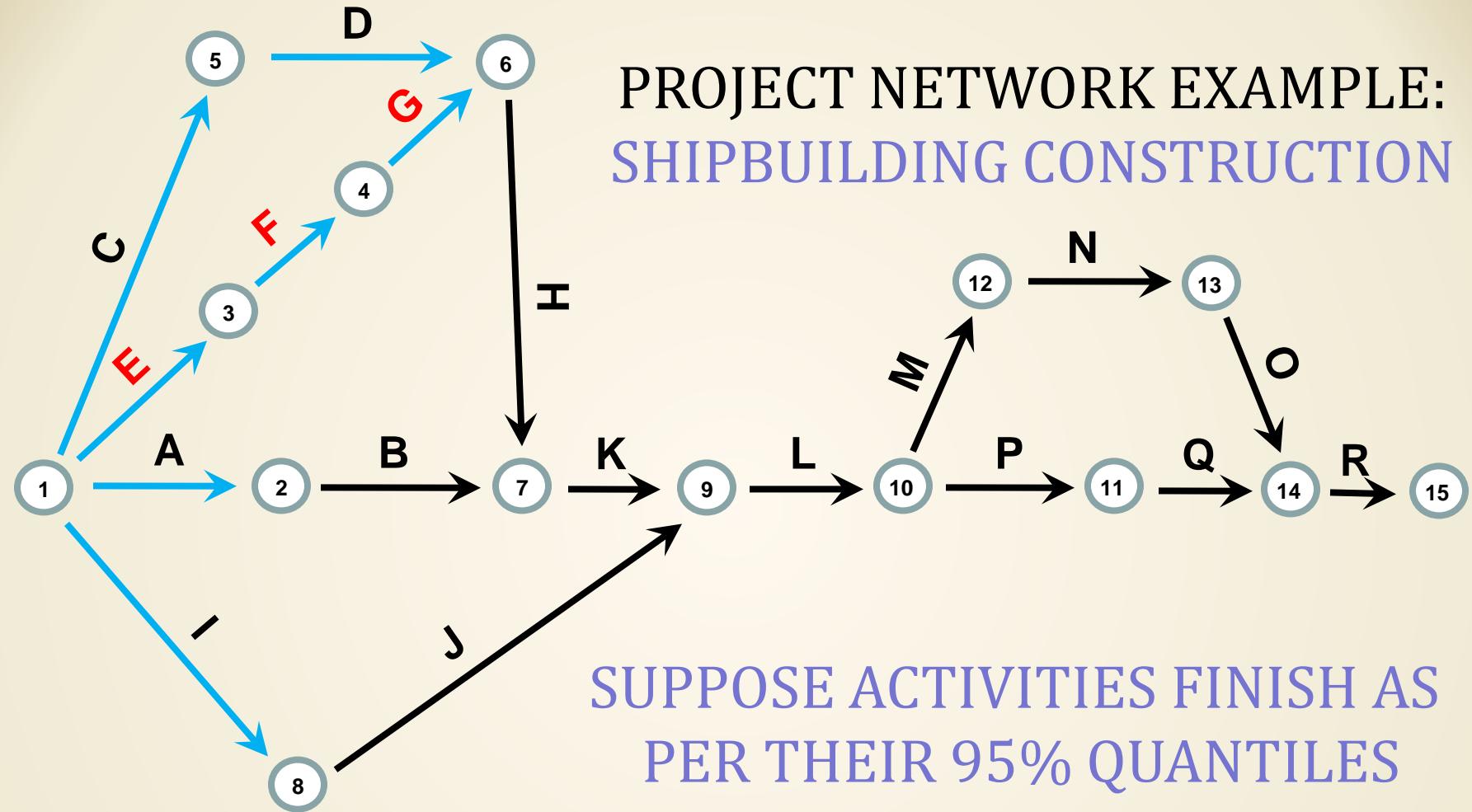
Start

0 20 40 60 80 100 120 140 160 180 200

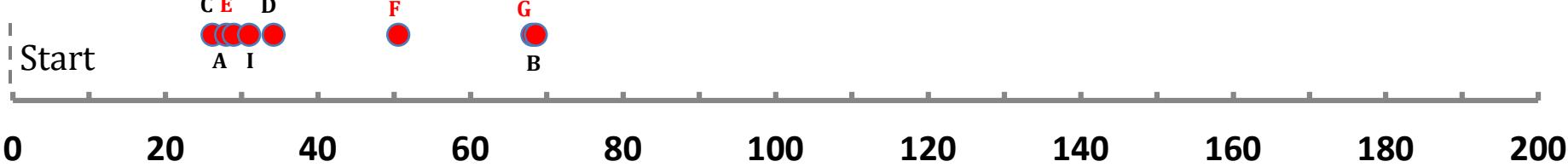
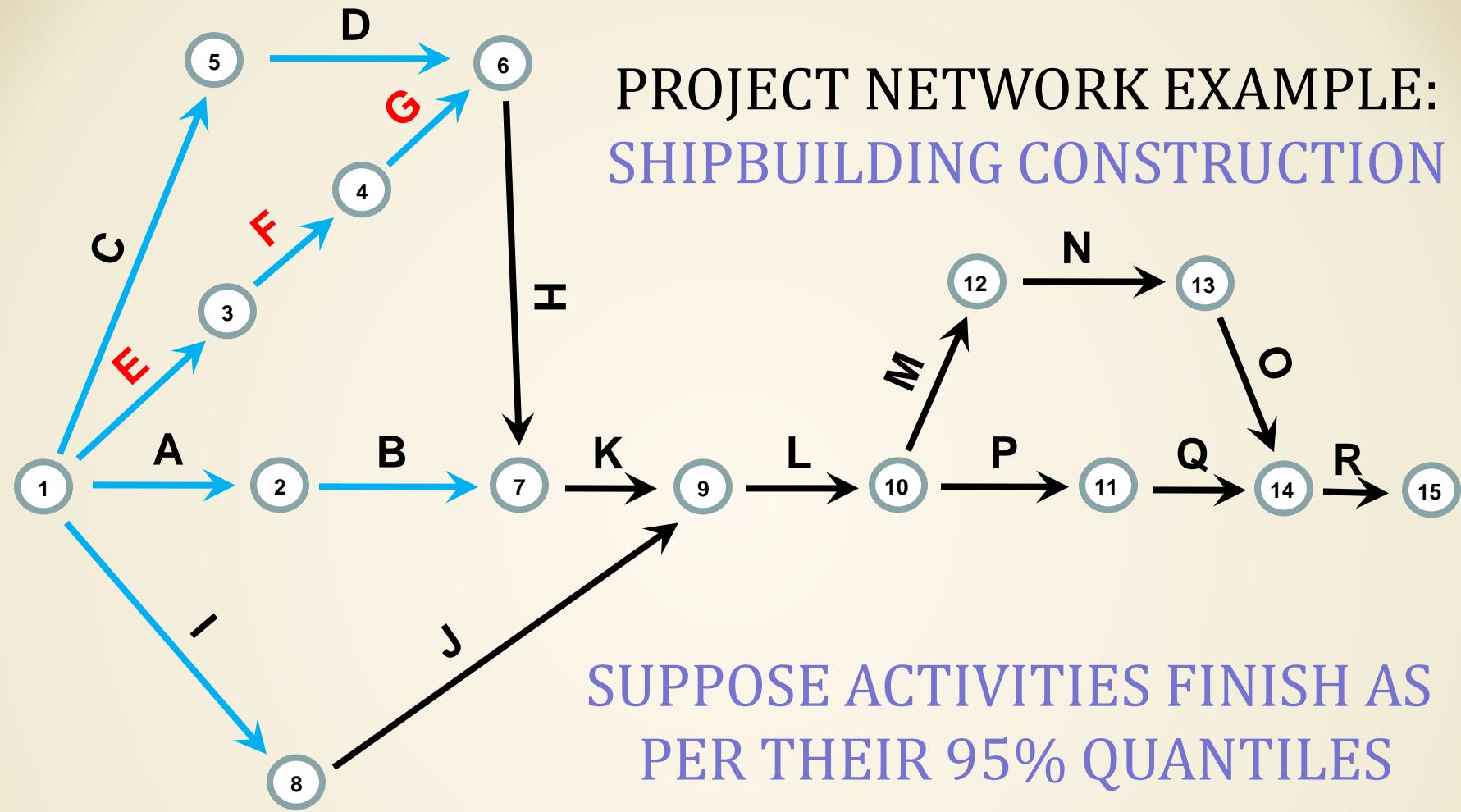
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



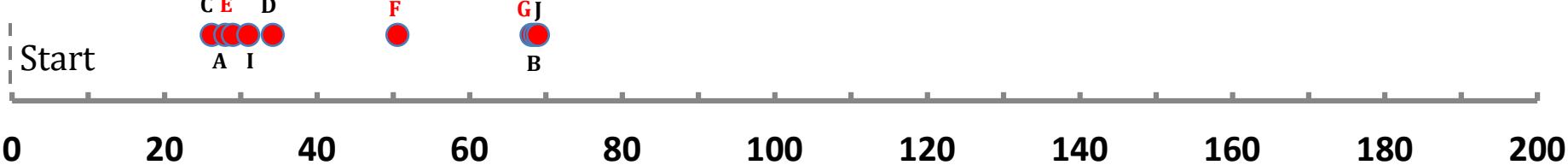
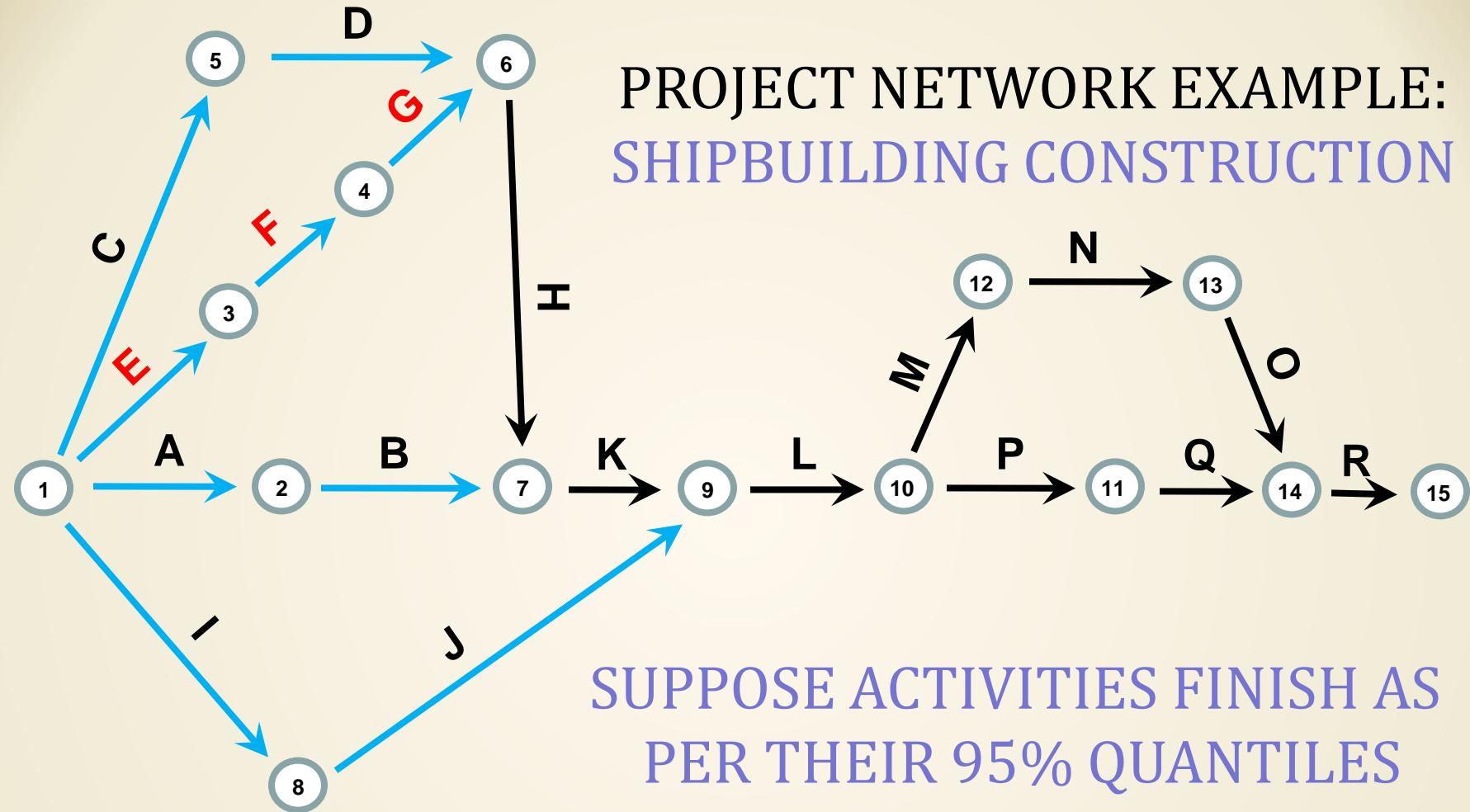
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



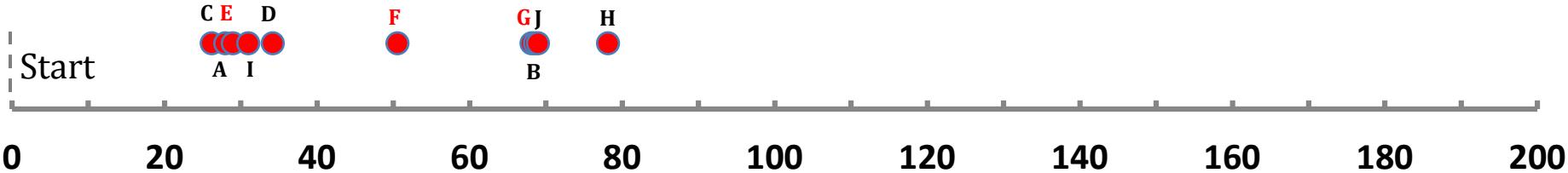
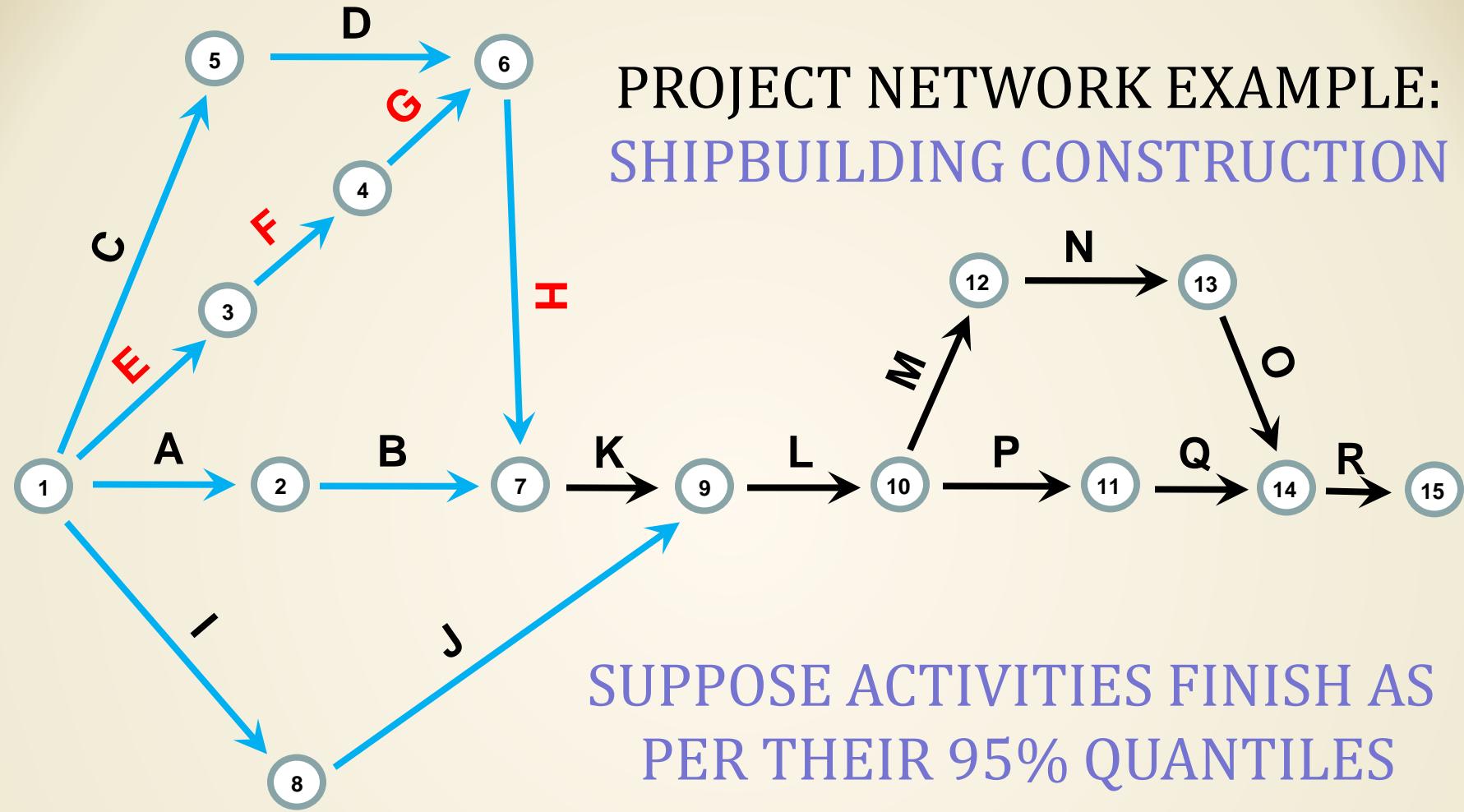
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



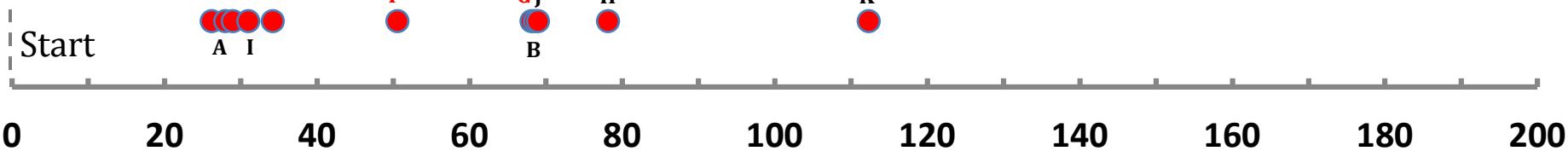
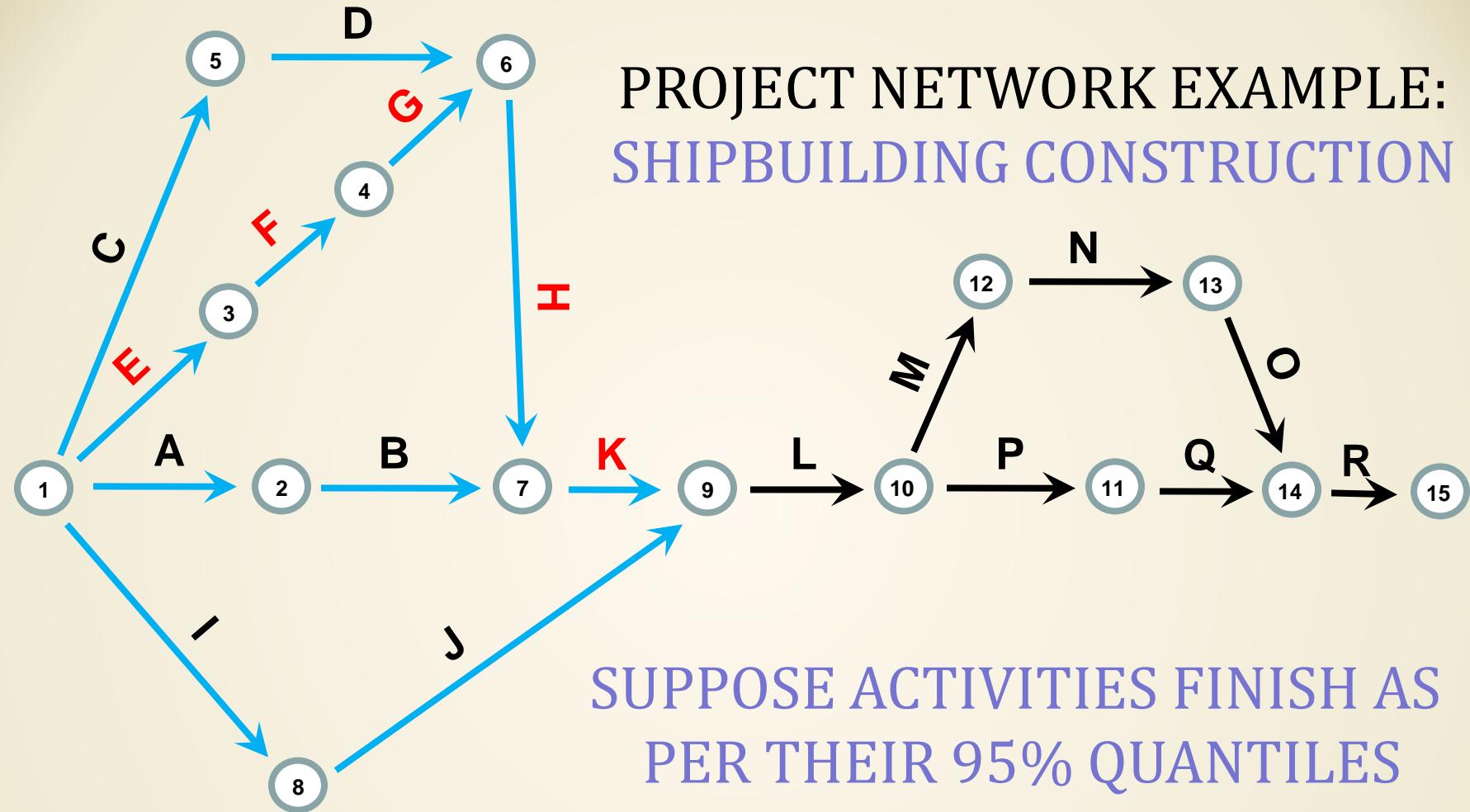
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



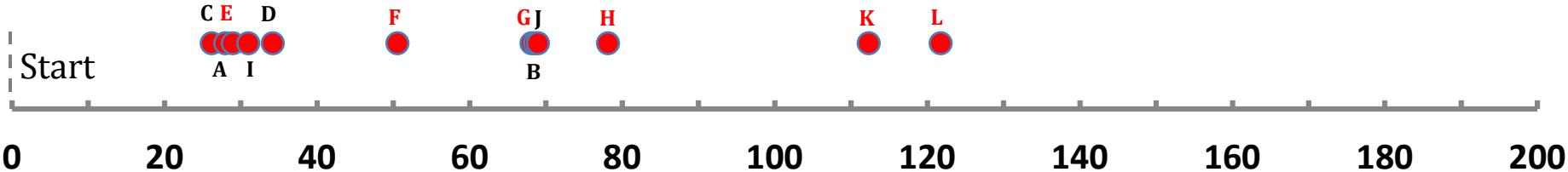
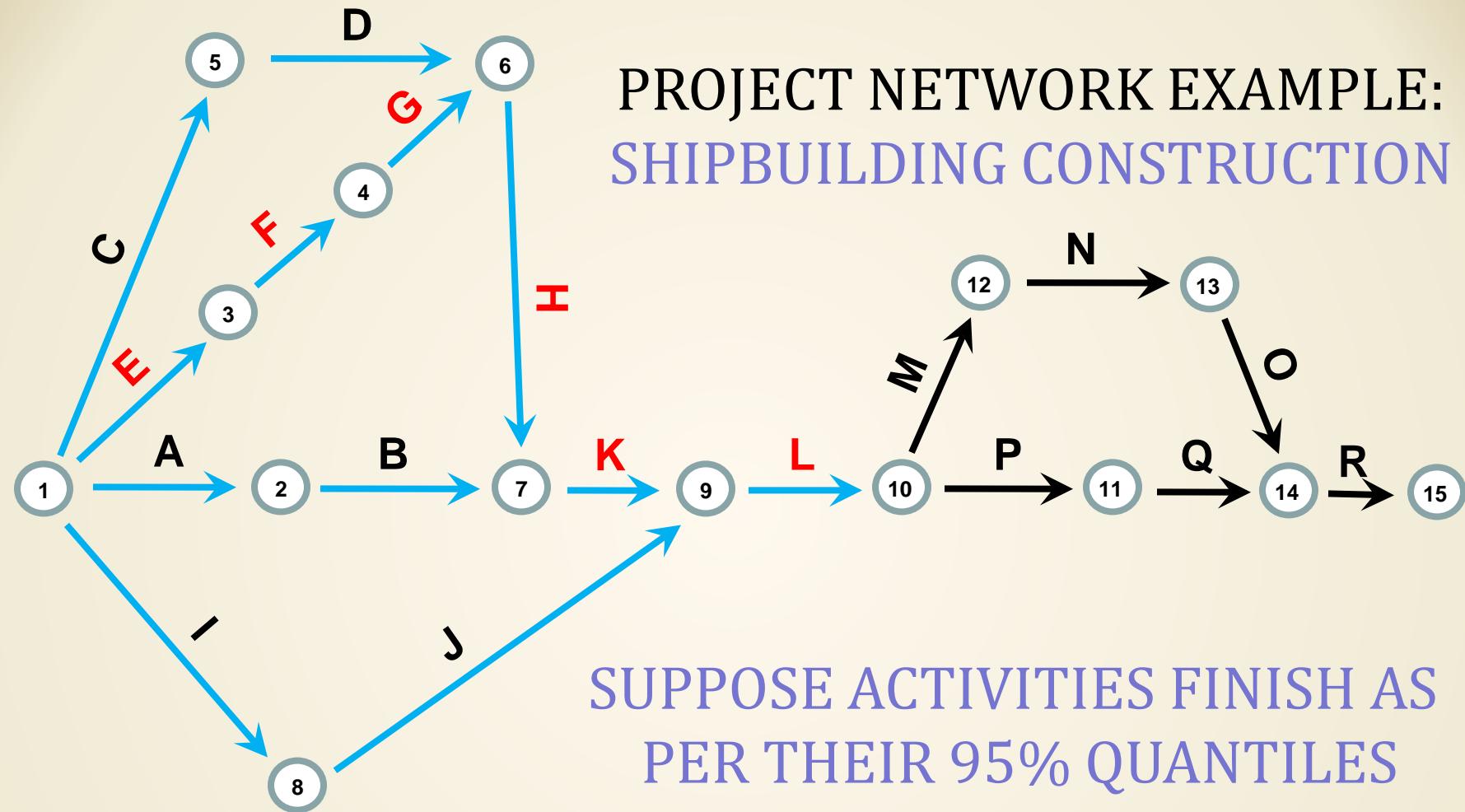
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



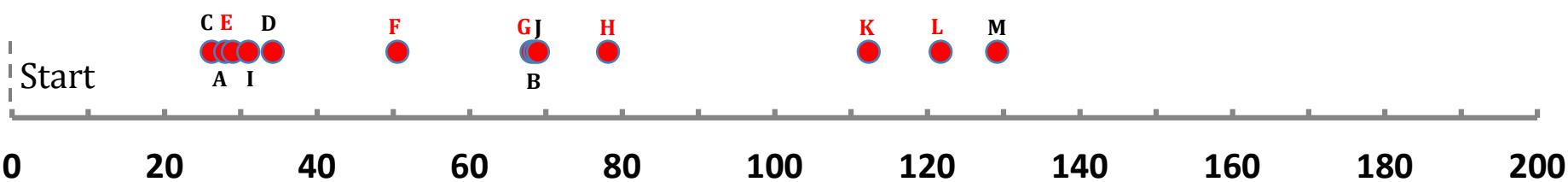
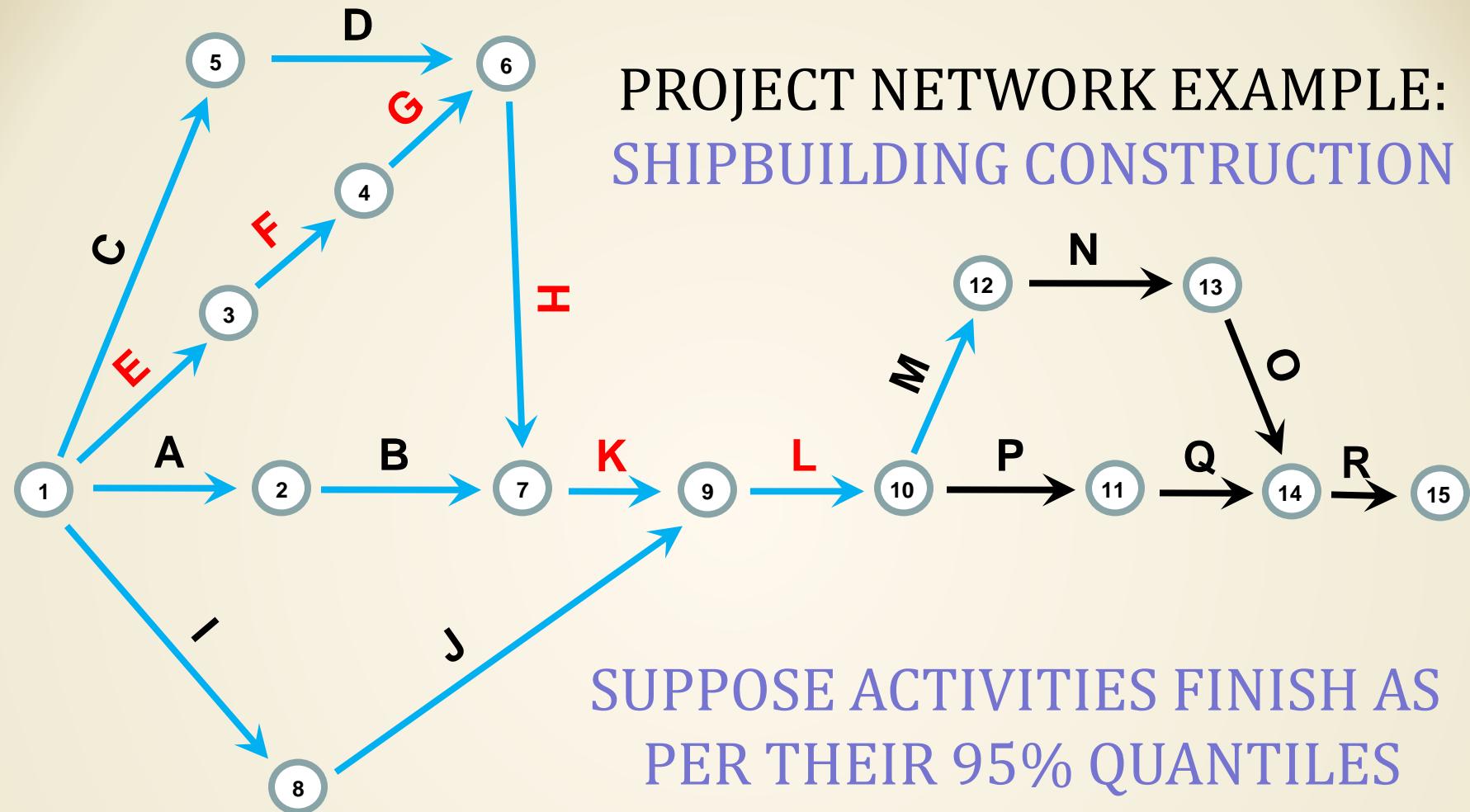
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



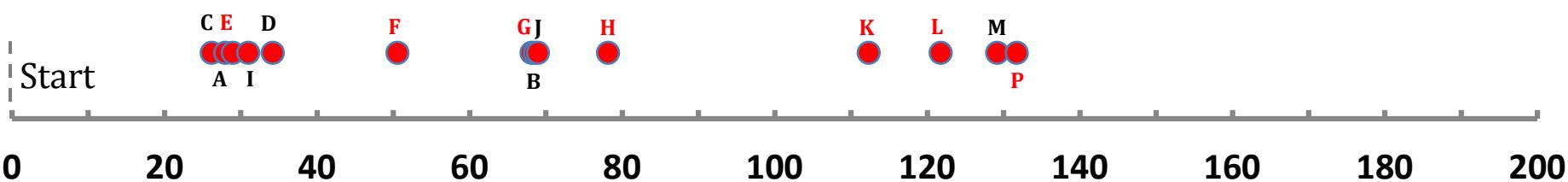
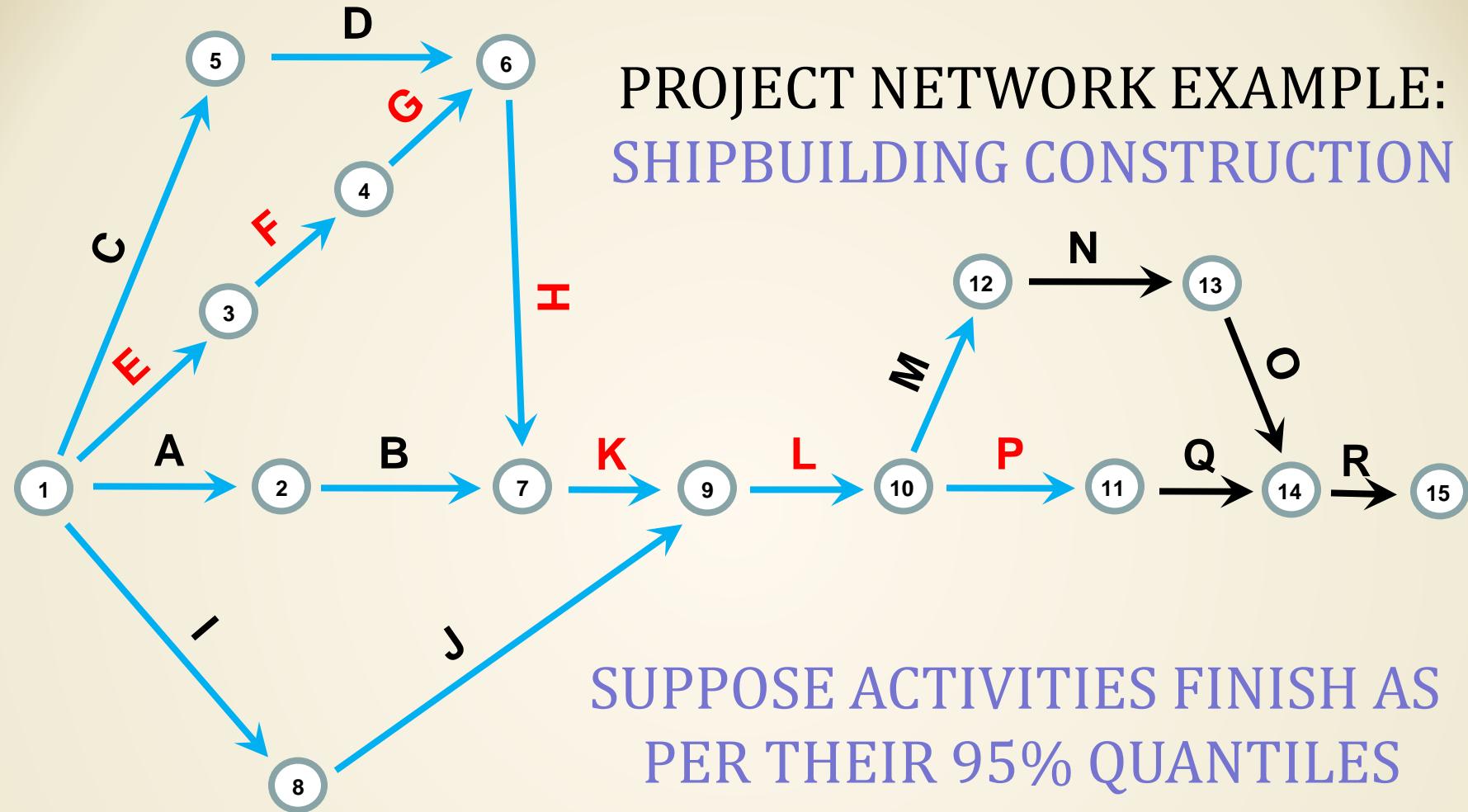
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



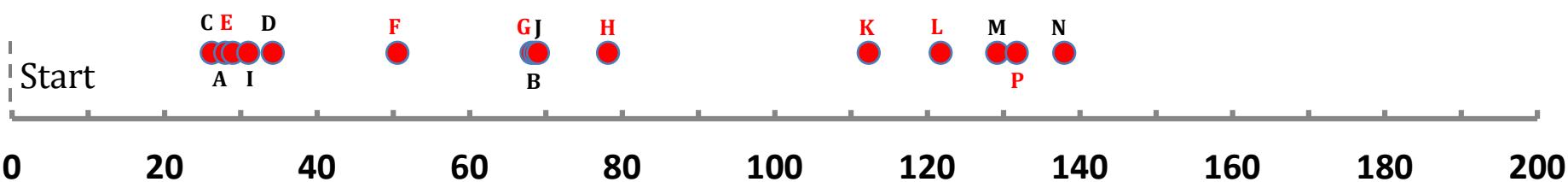
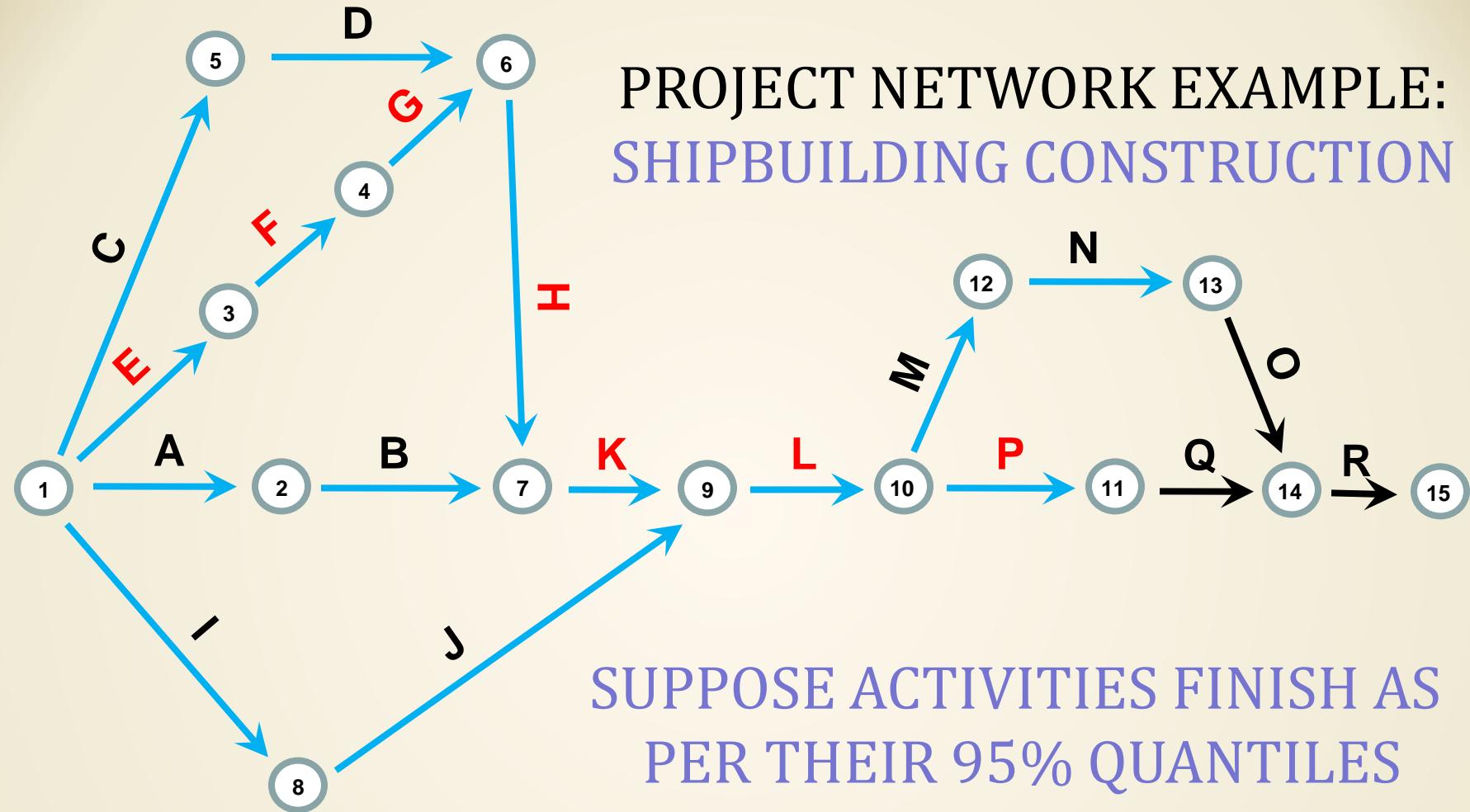
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



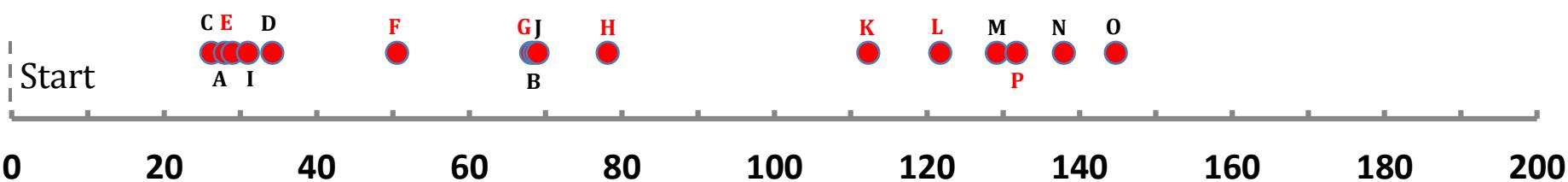
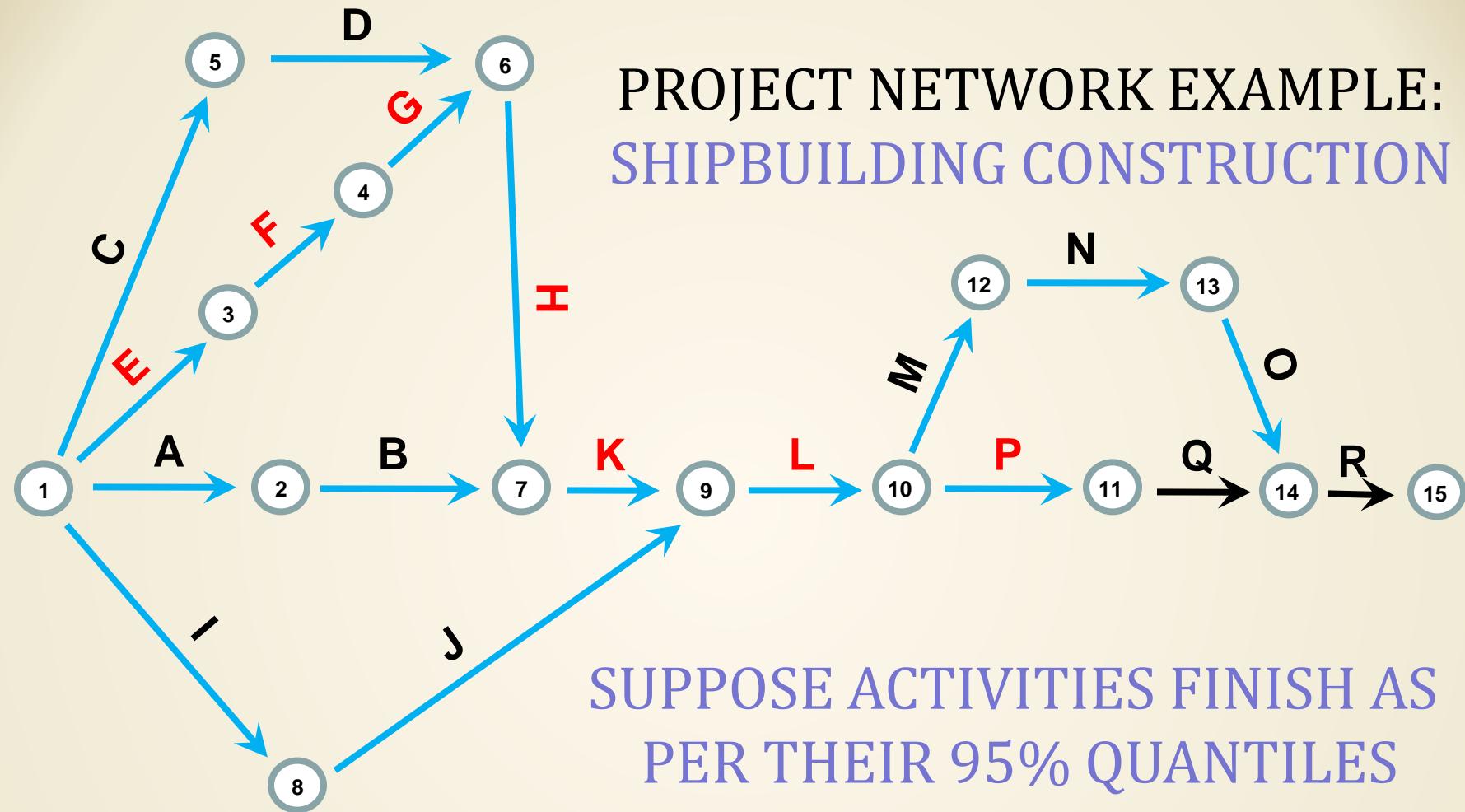
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



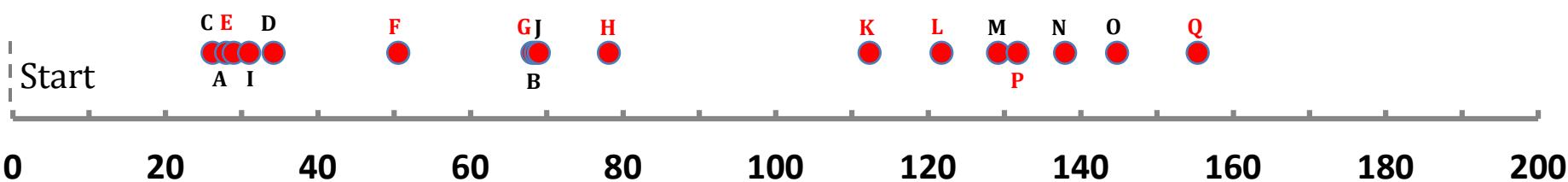
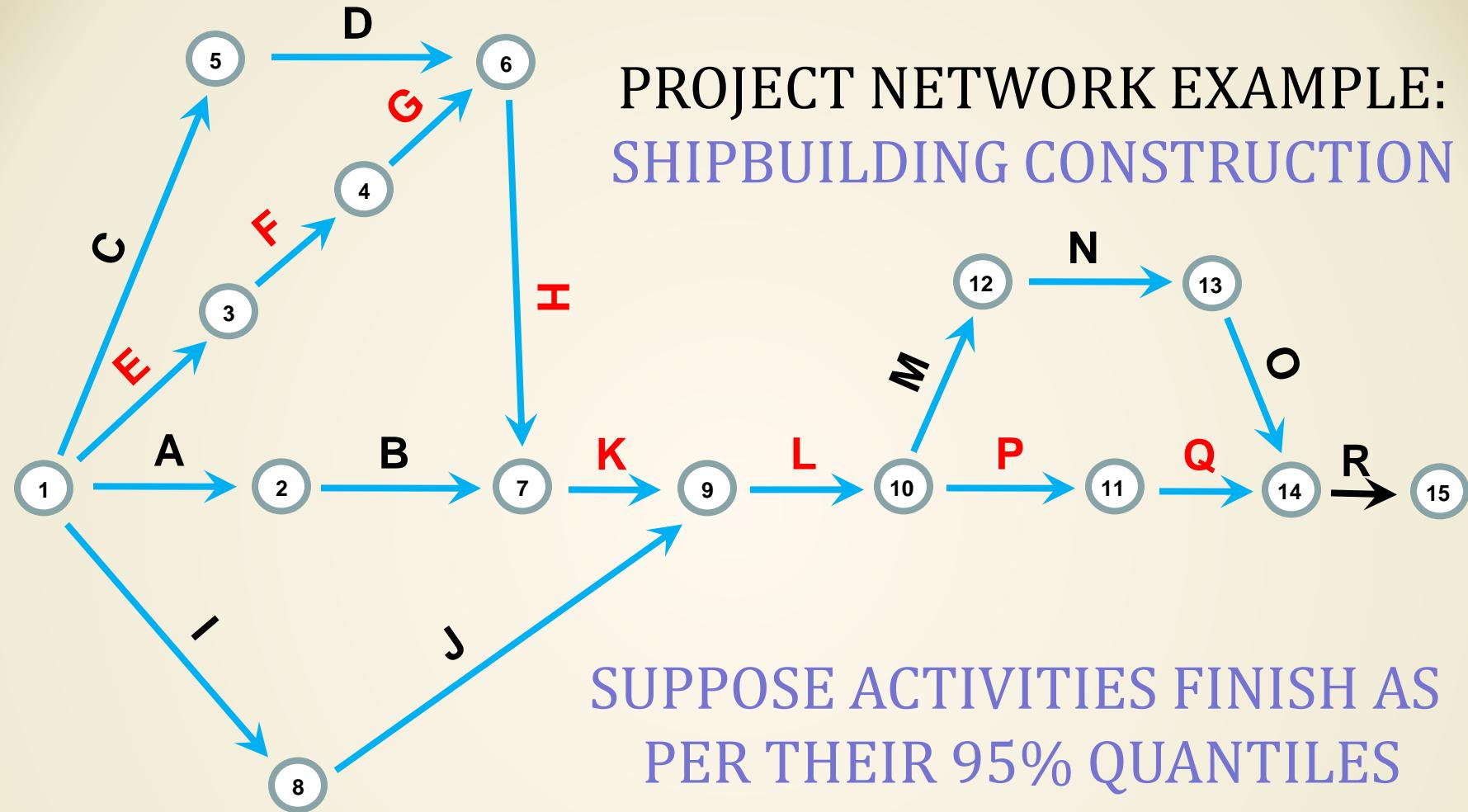
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



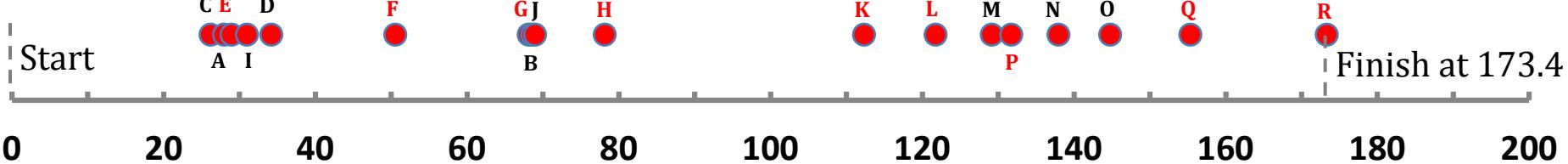
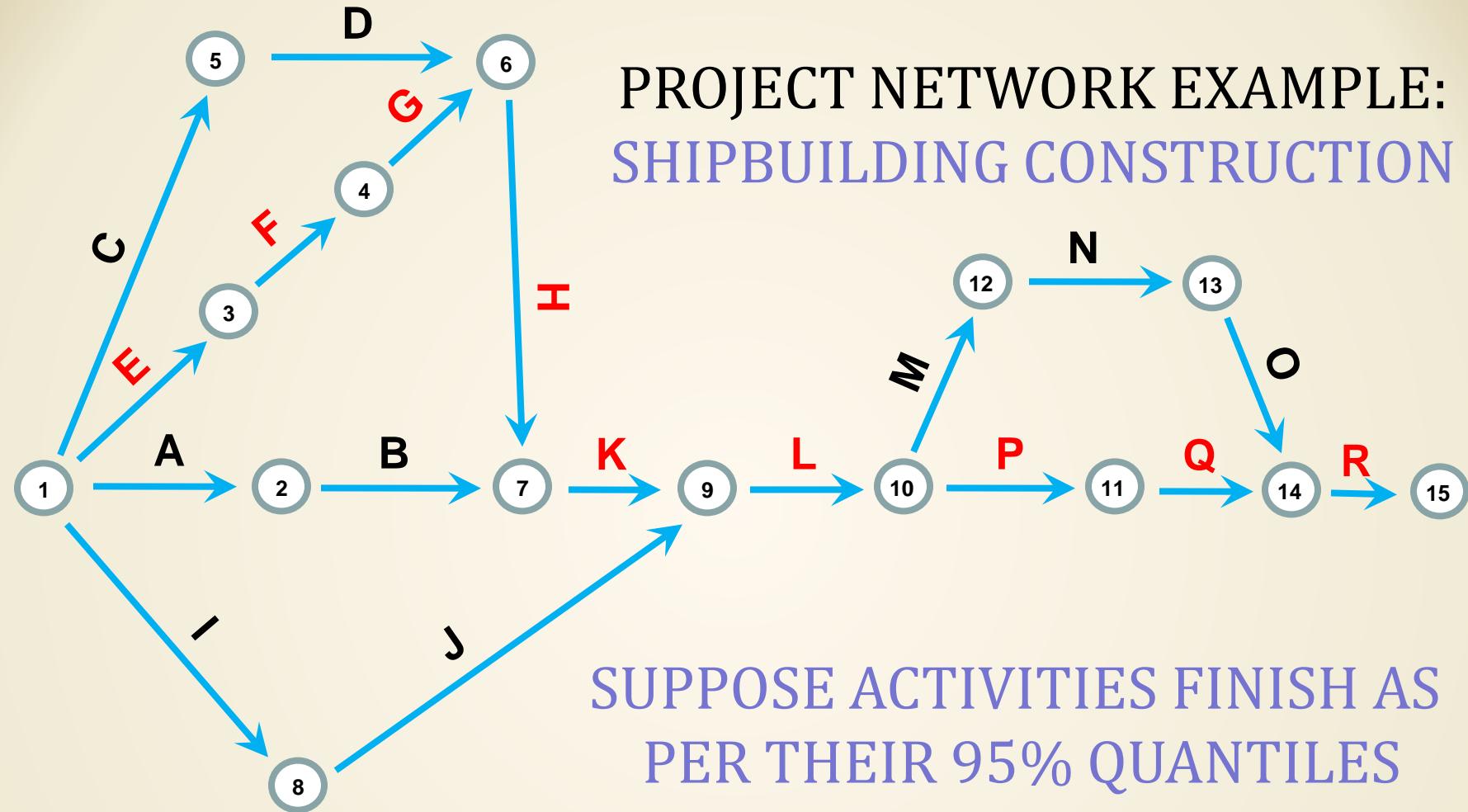
PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION



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PROJECT NETWORK EXAMPLE: SHIPBUILDING CONSTRUCTION

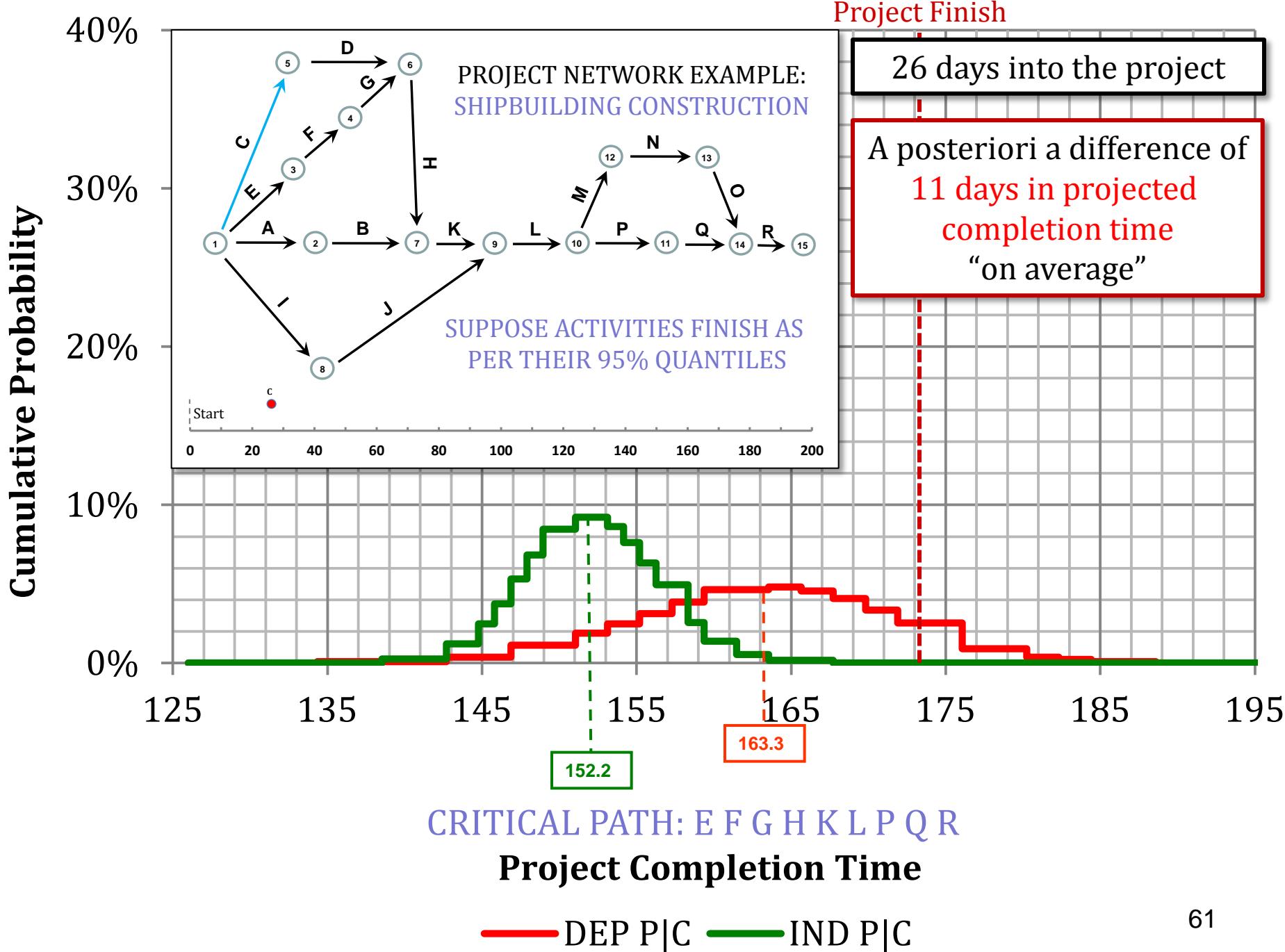


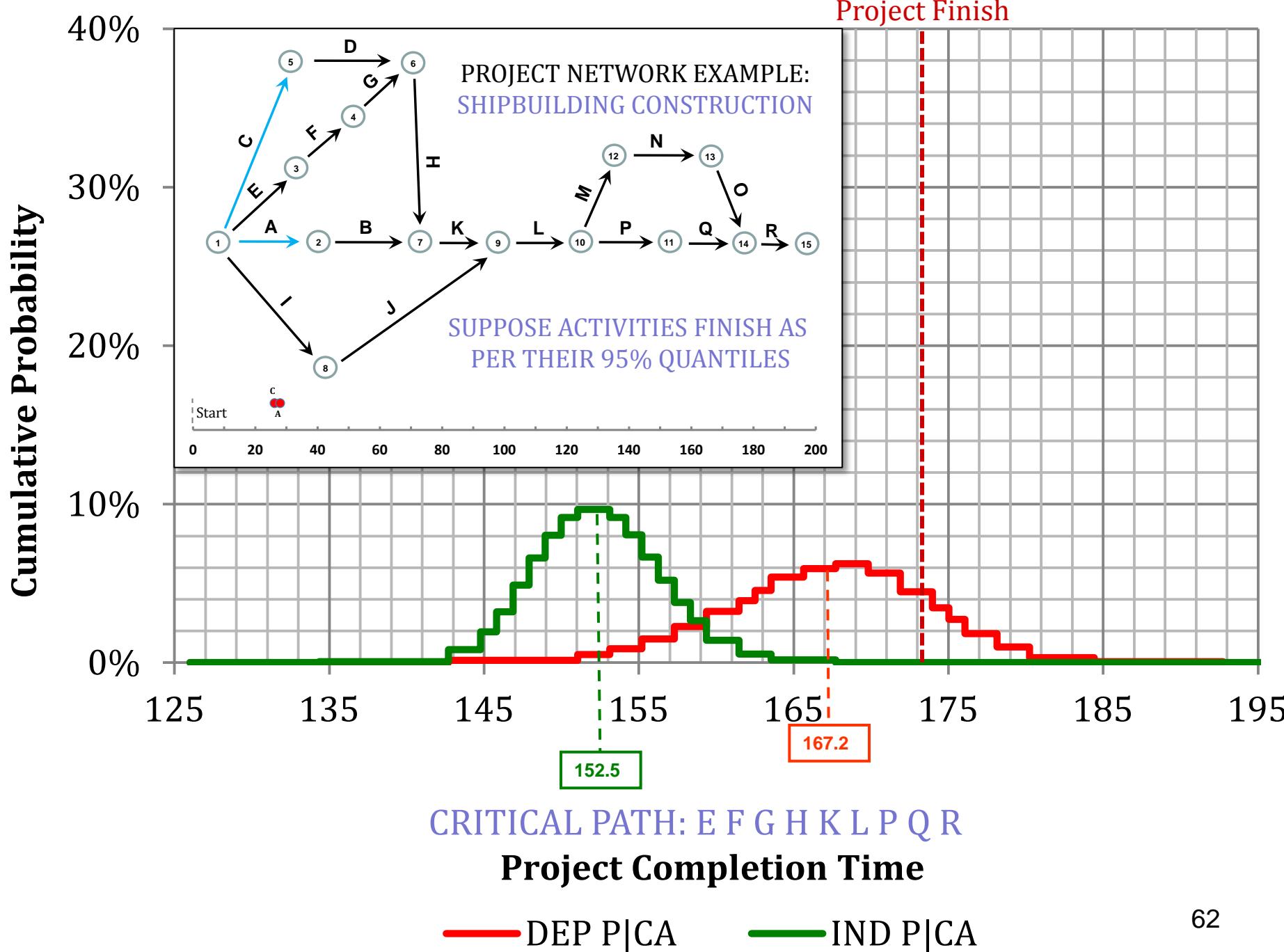
Our objective is to re-evaluate/monitor remaining
Project Completion Time Uncertainty
as activities finish one by one

and

To compare the potential implication of neglecting
Activity Statistical Dependence amongst
remaining activities to be completed.

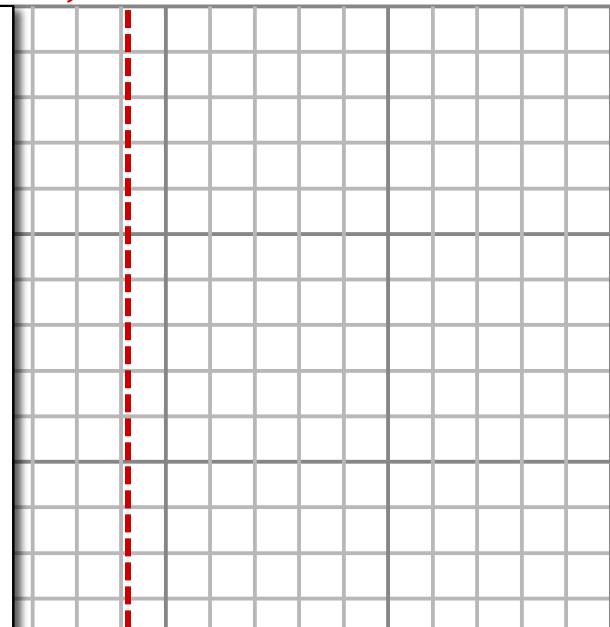
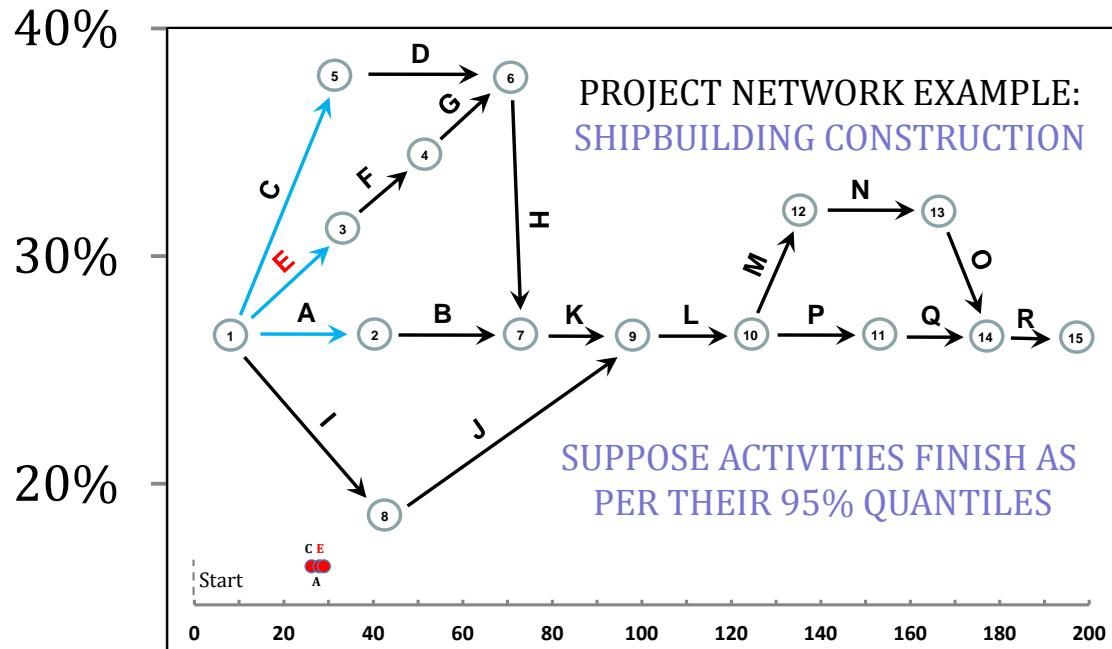
In this case study average **activity correlation is approximately 0.5**. Effects to be observed would be amplified at higher correlation levels.





Project Finish

Cumulative Probability

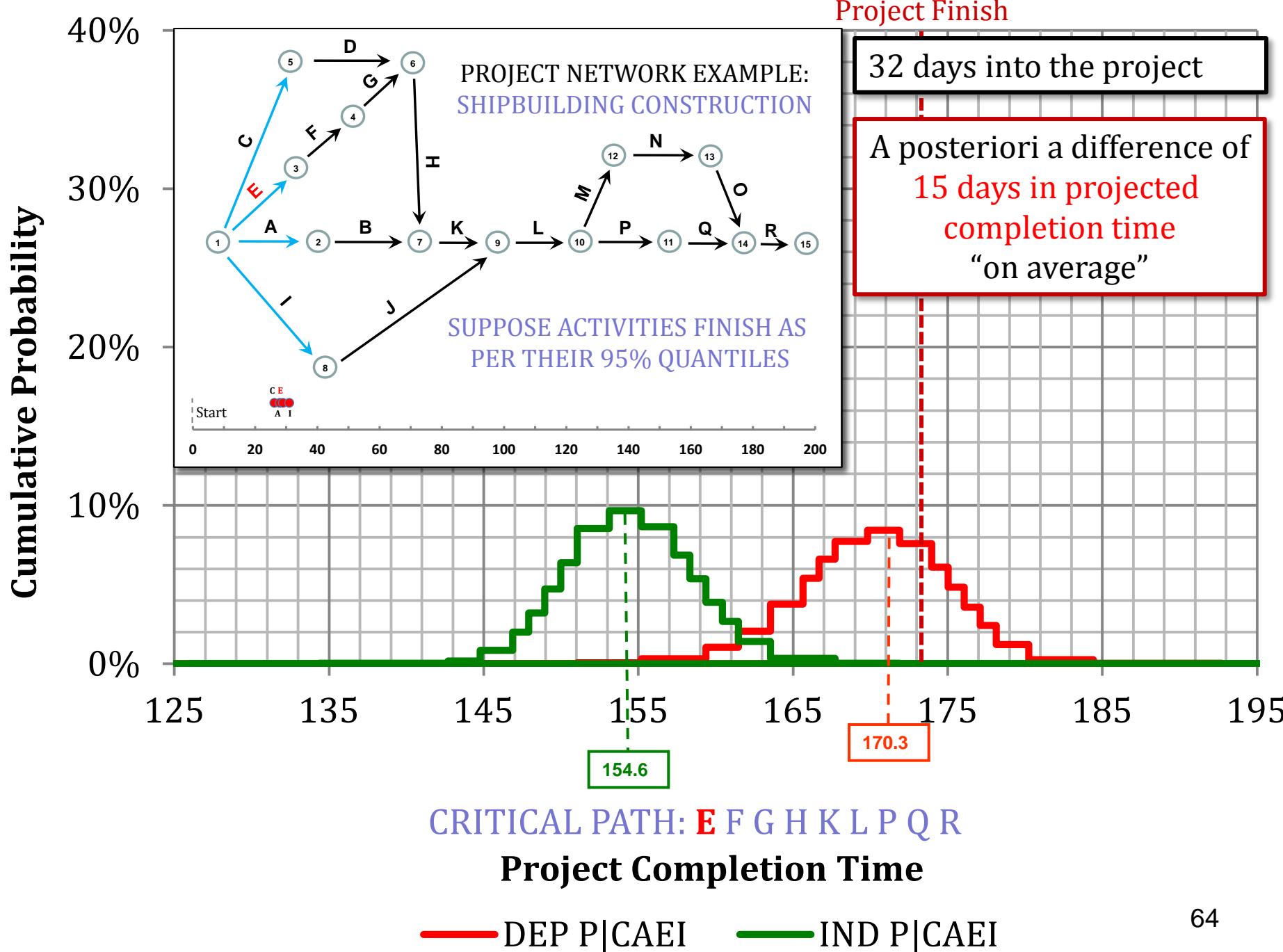


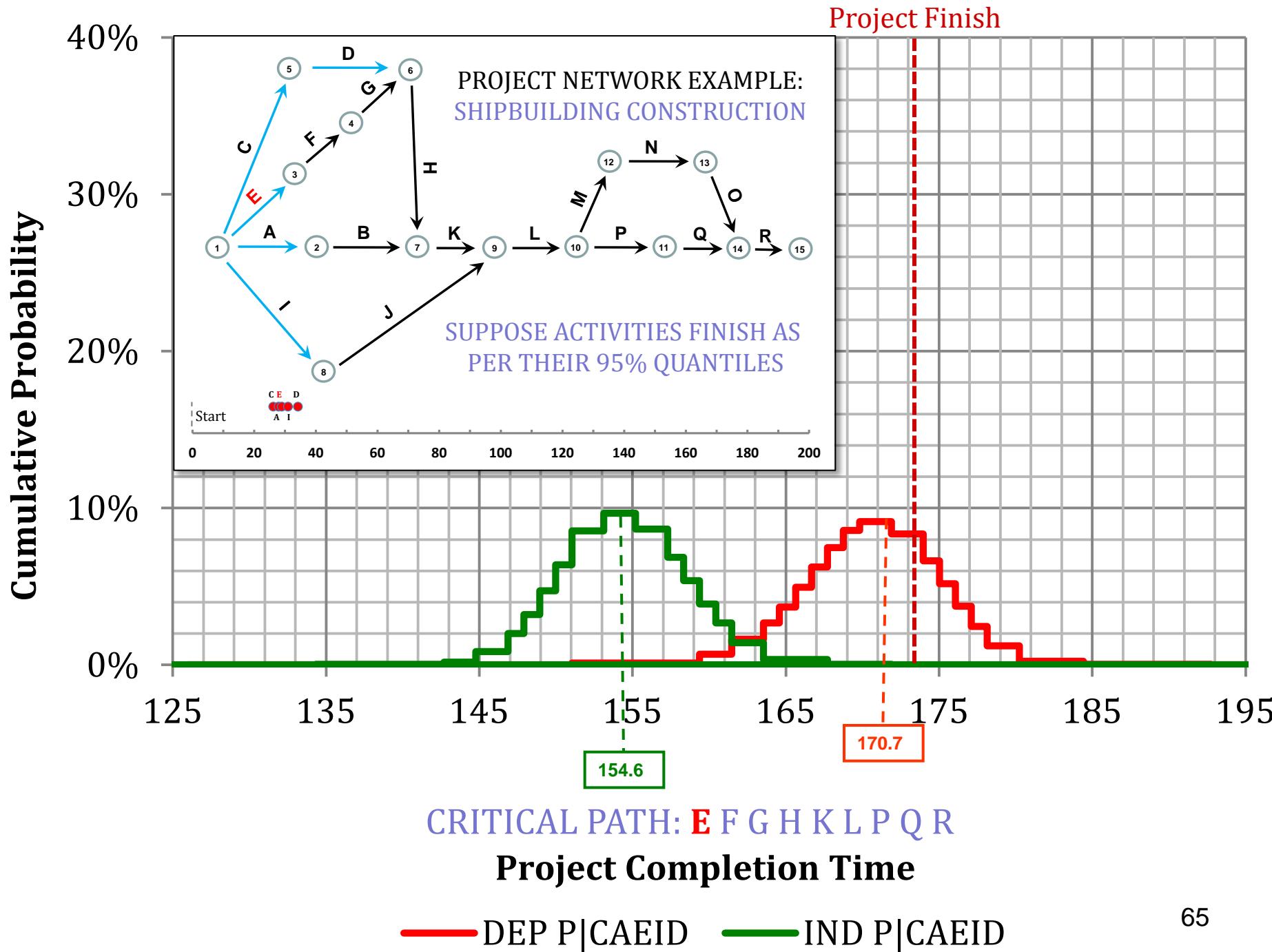
CRITICAL PATH: E F G H K L P Q R

Project Completion Time

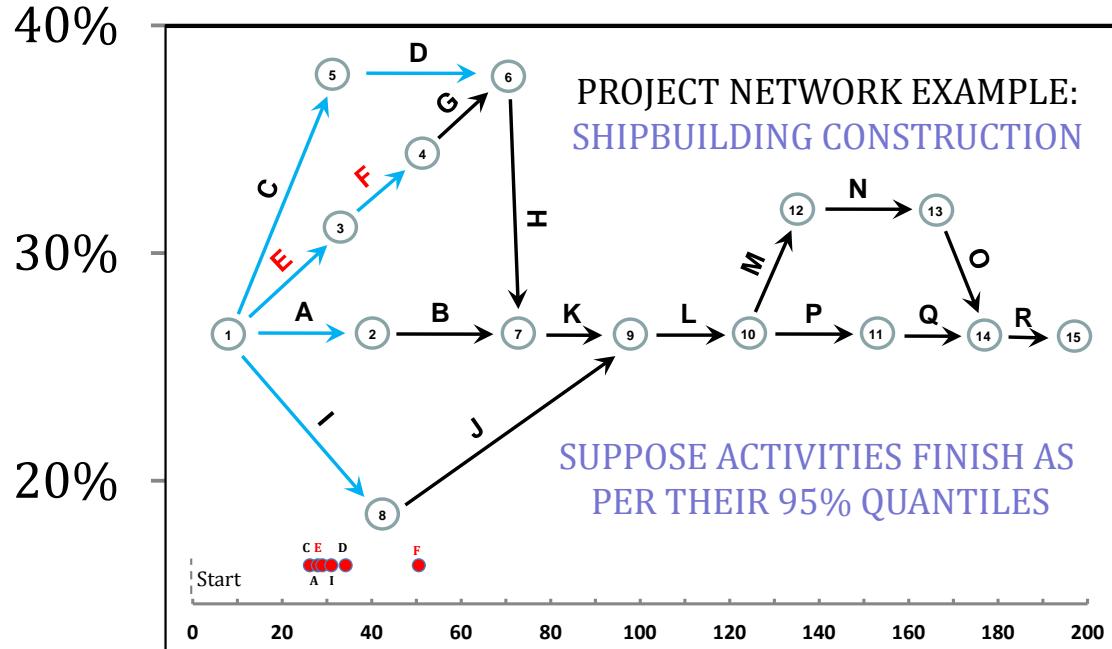
DEP P|CAE

IND P|CAE





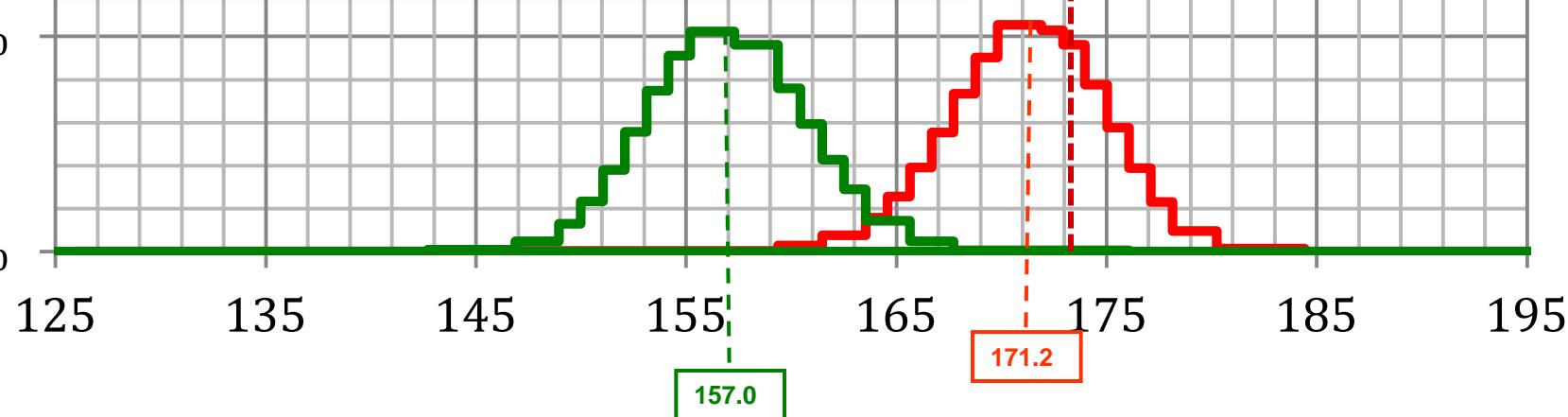
Cumulative Probability

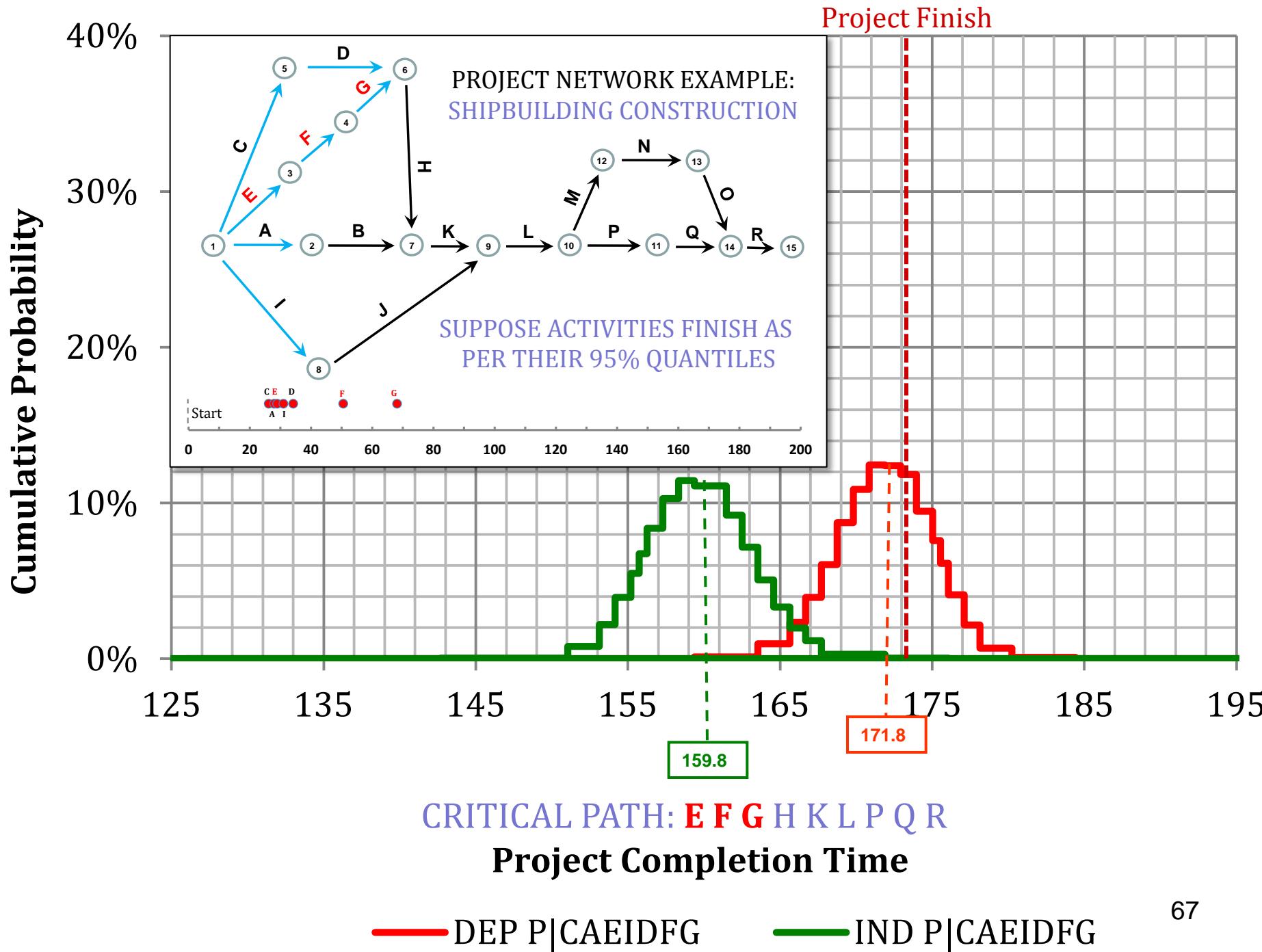


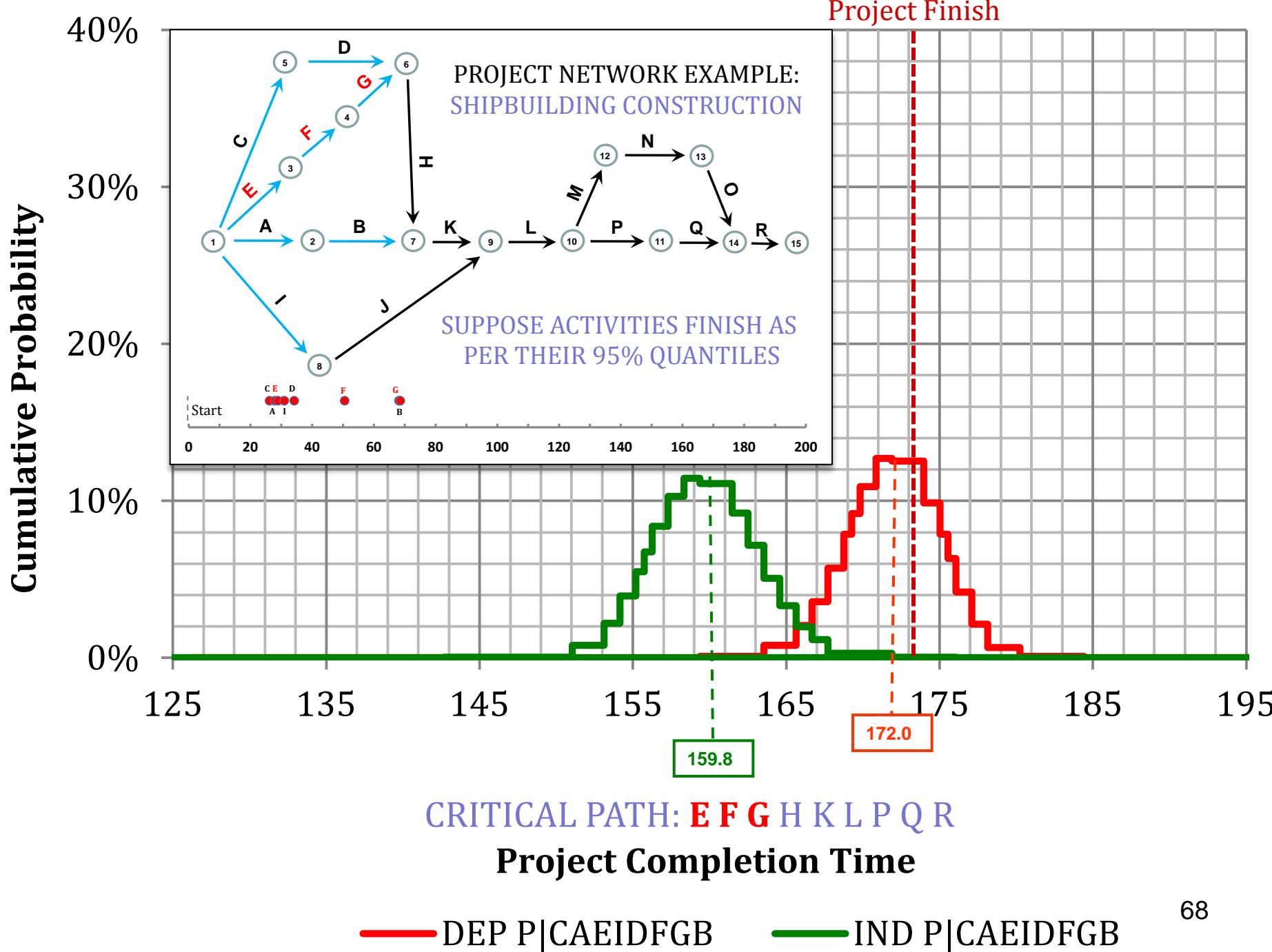
Project Finish

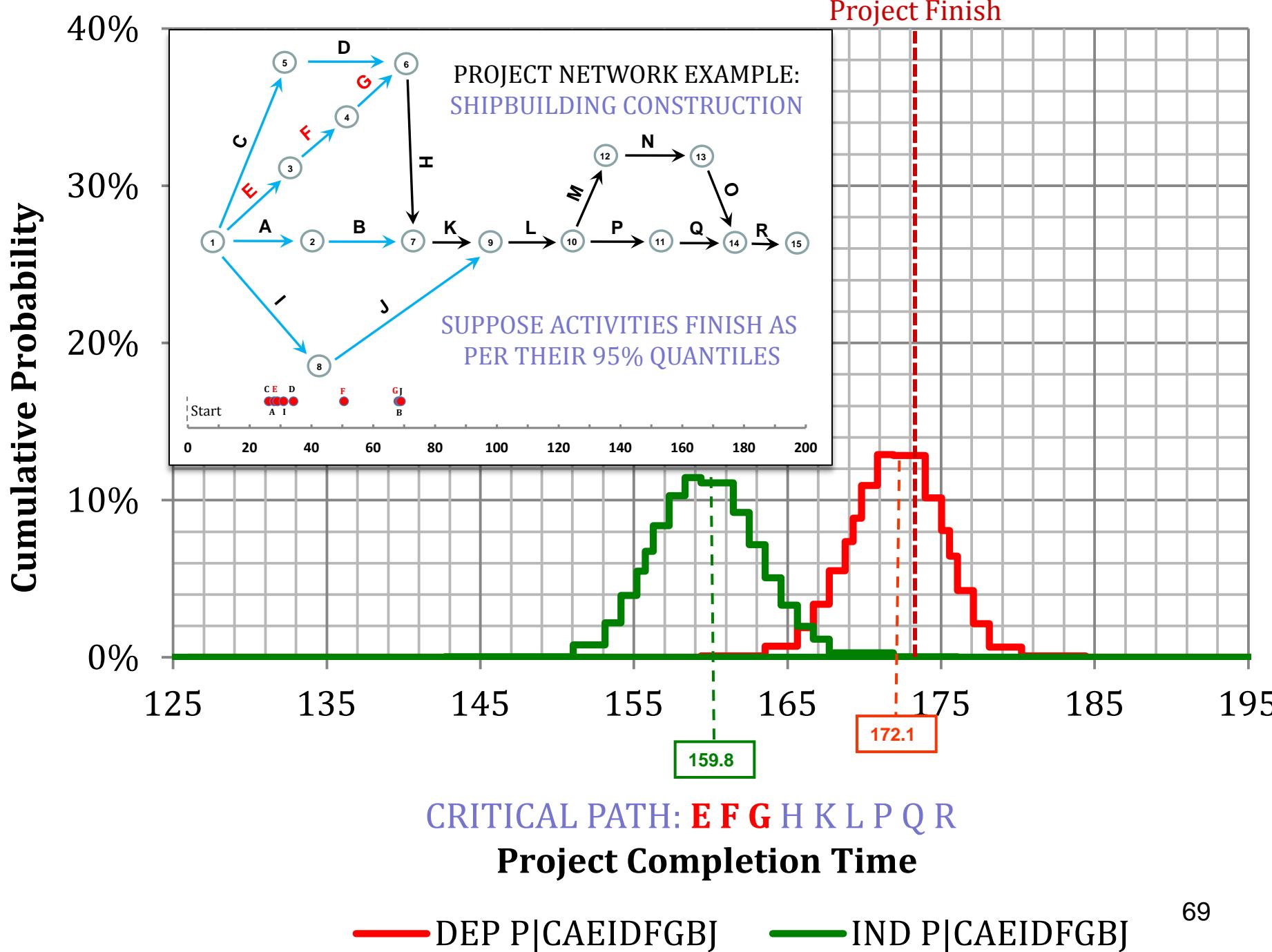
50 days into the project

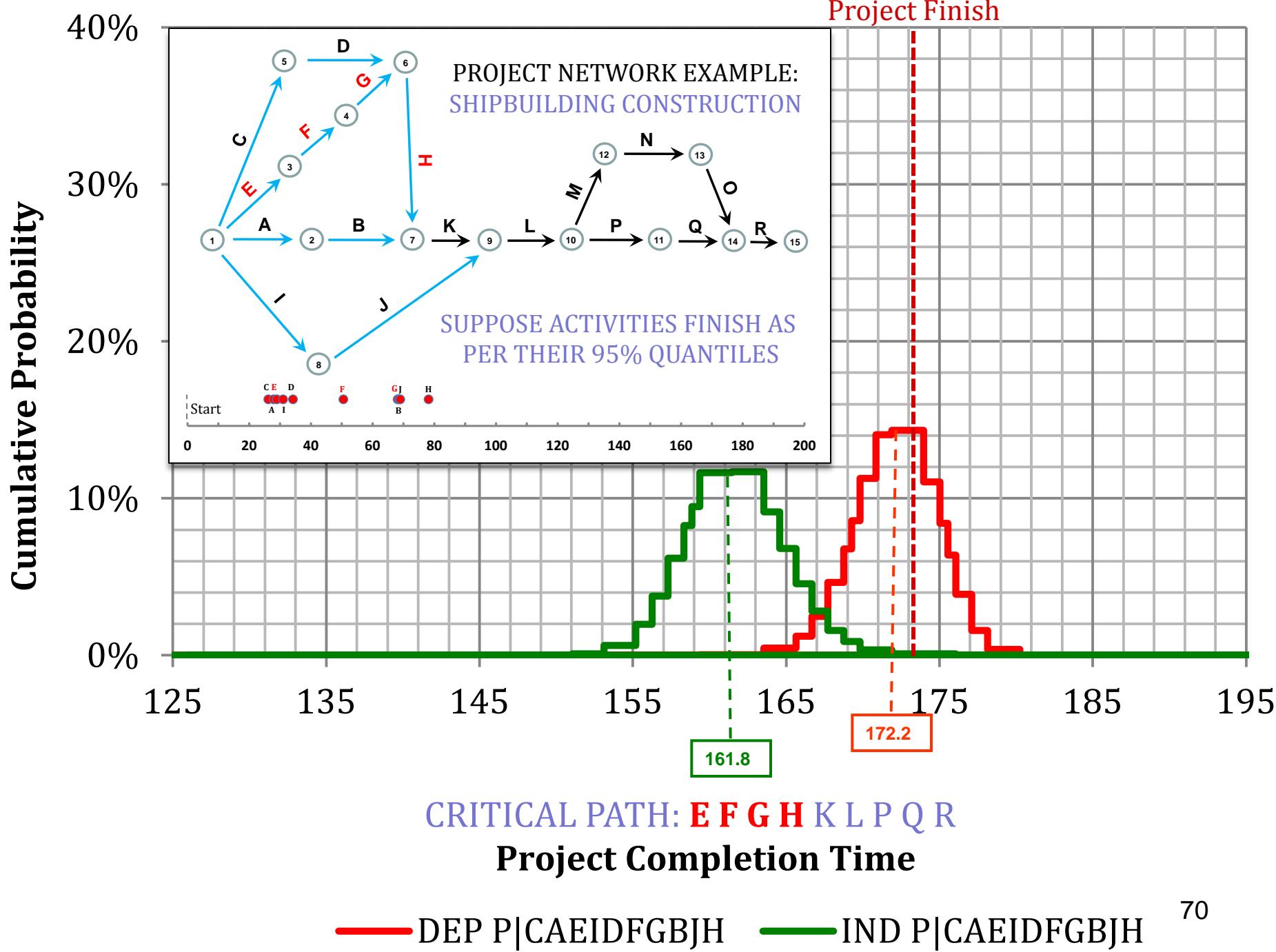
Project Completion Time
standard deviation
is about the same !!!

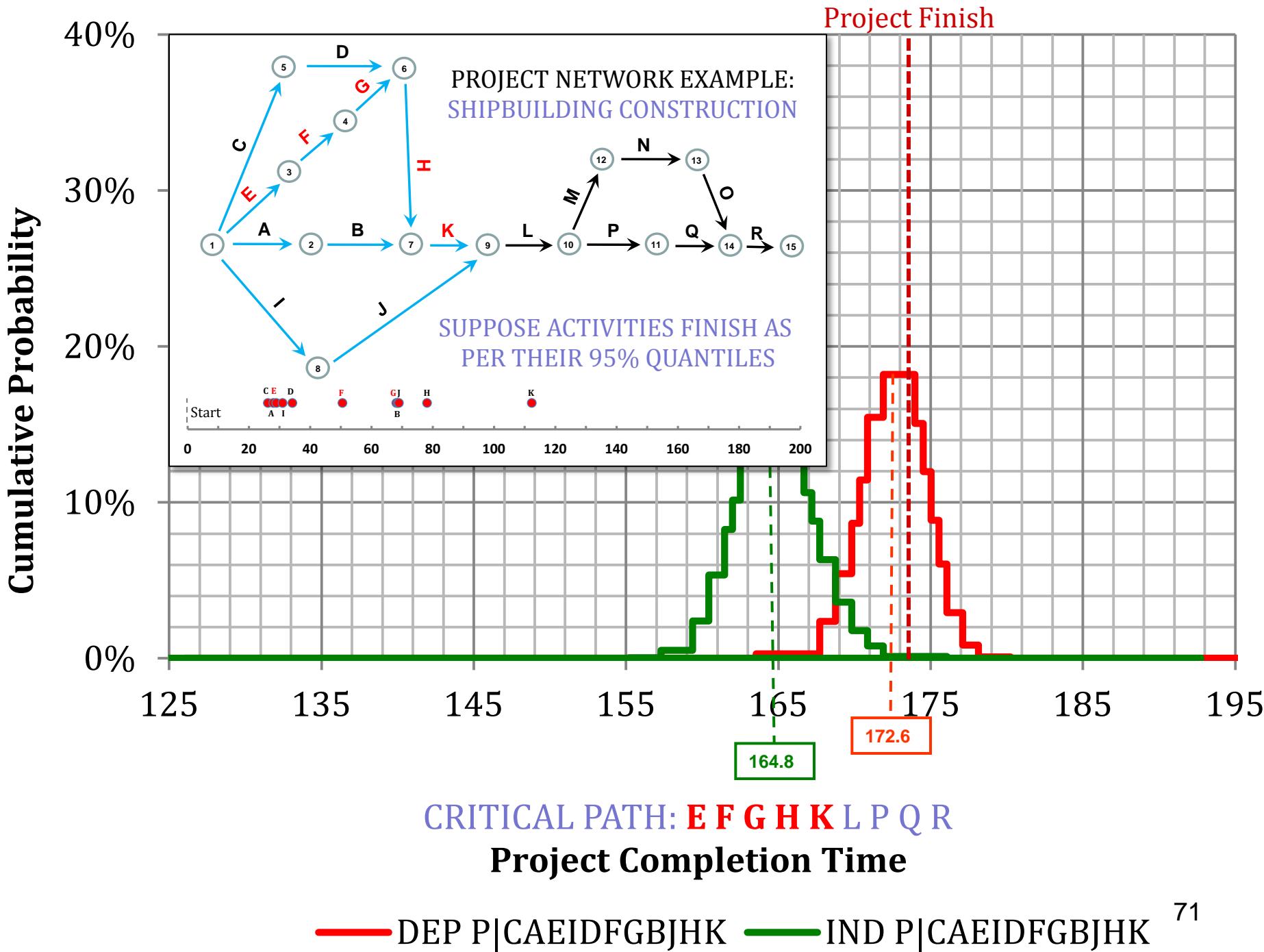


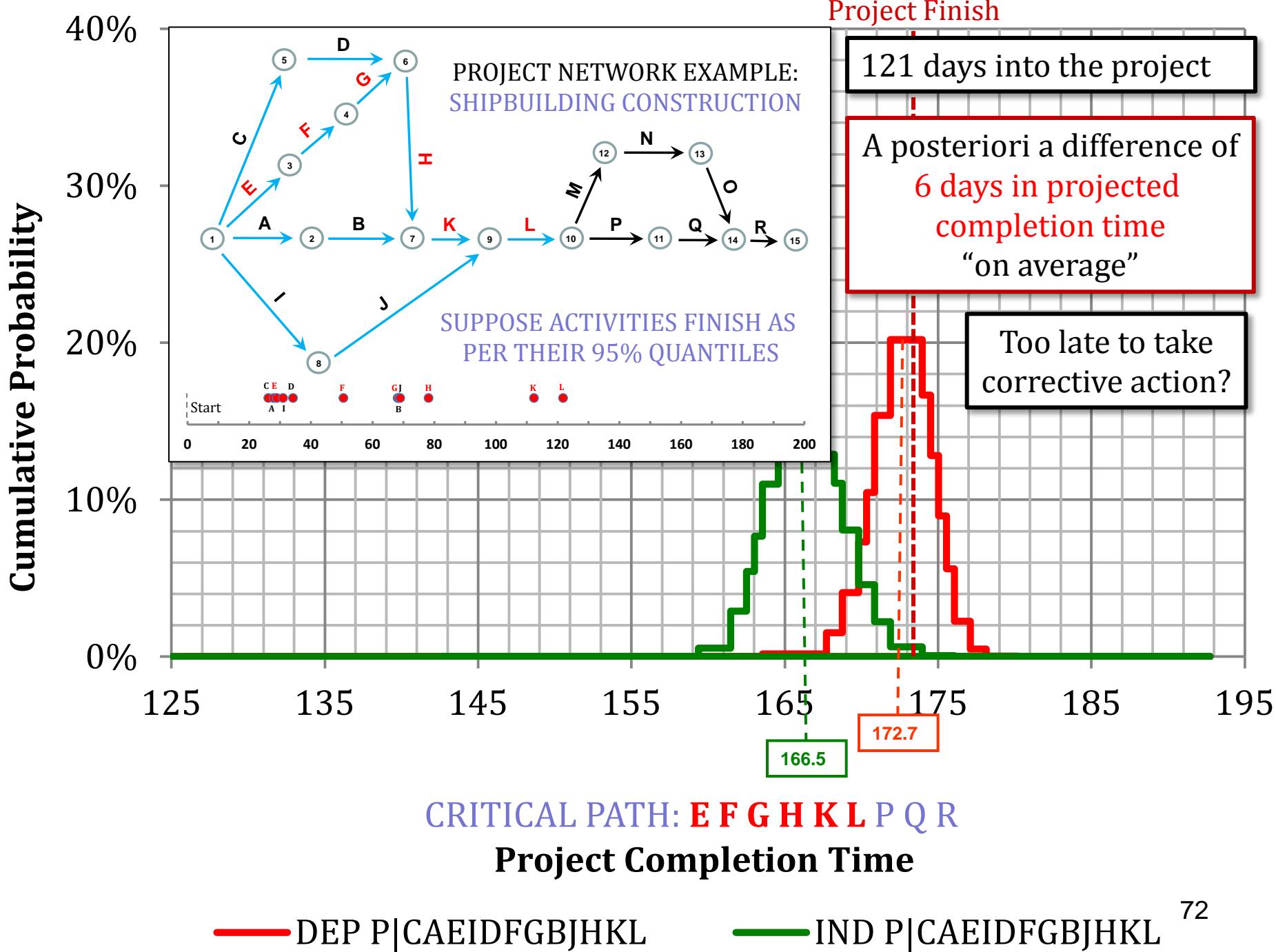


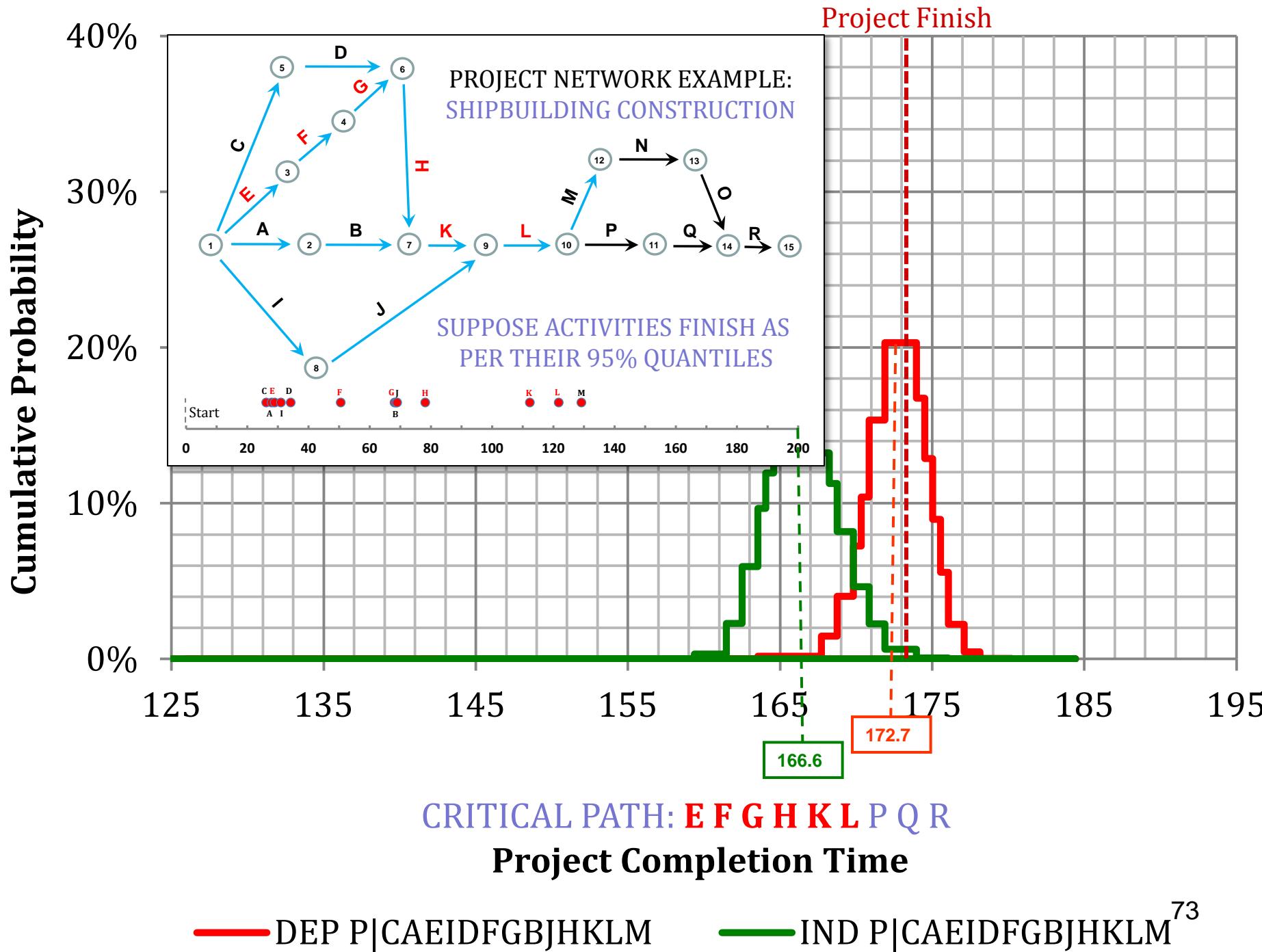


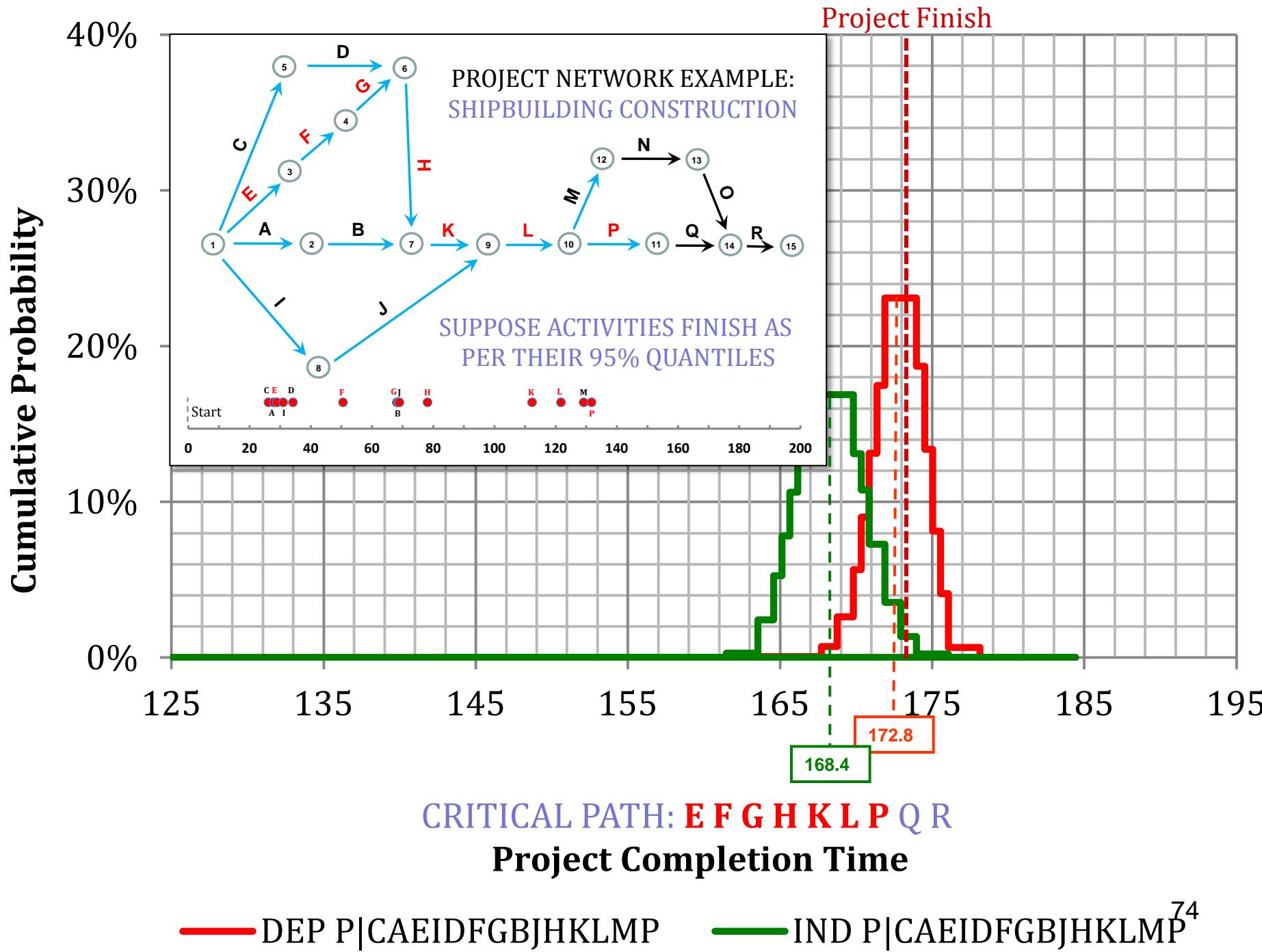


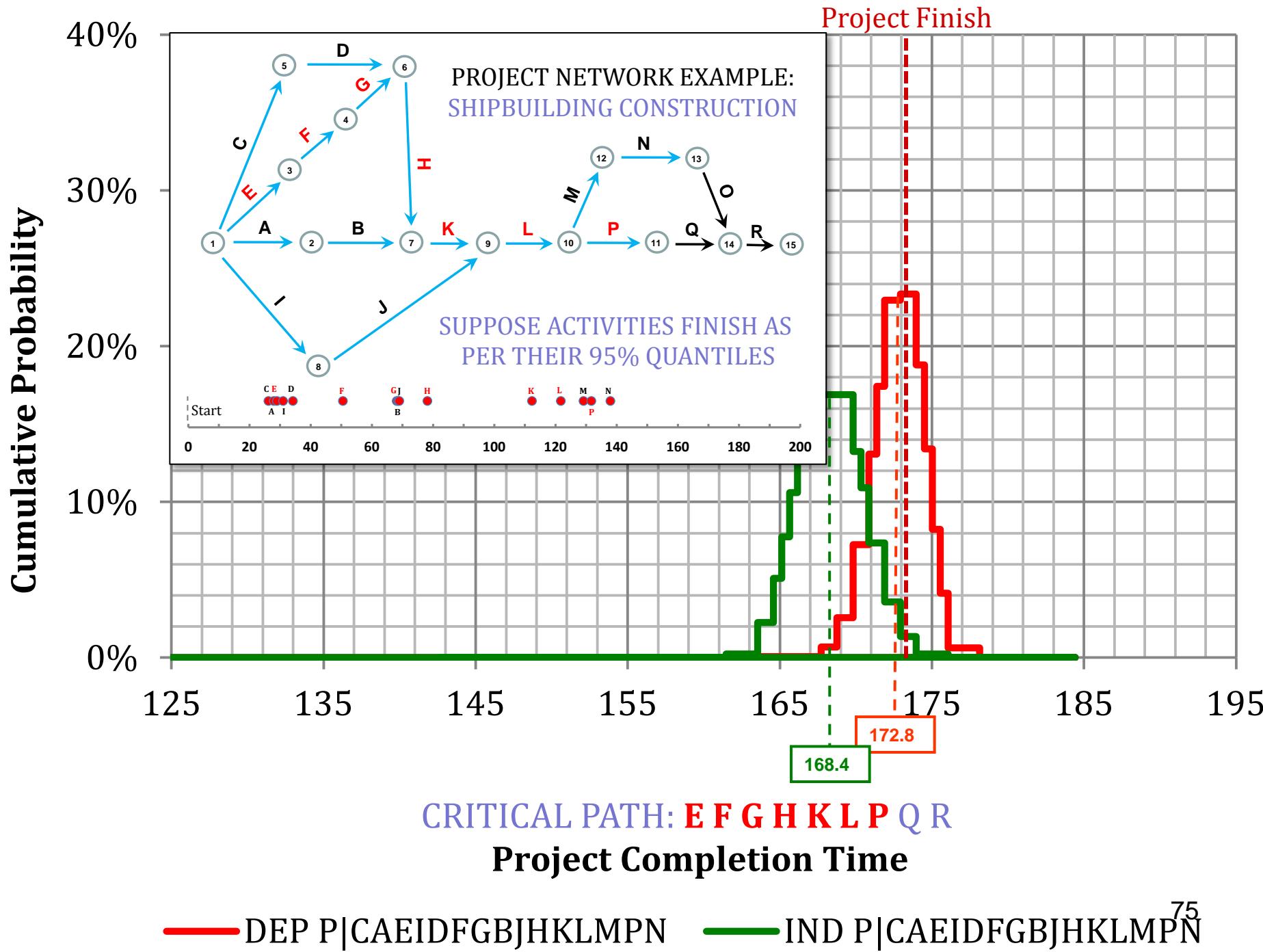


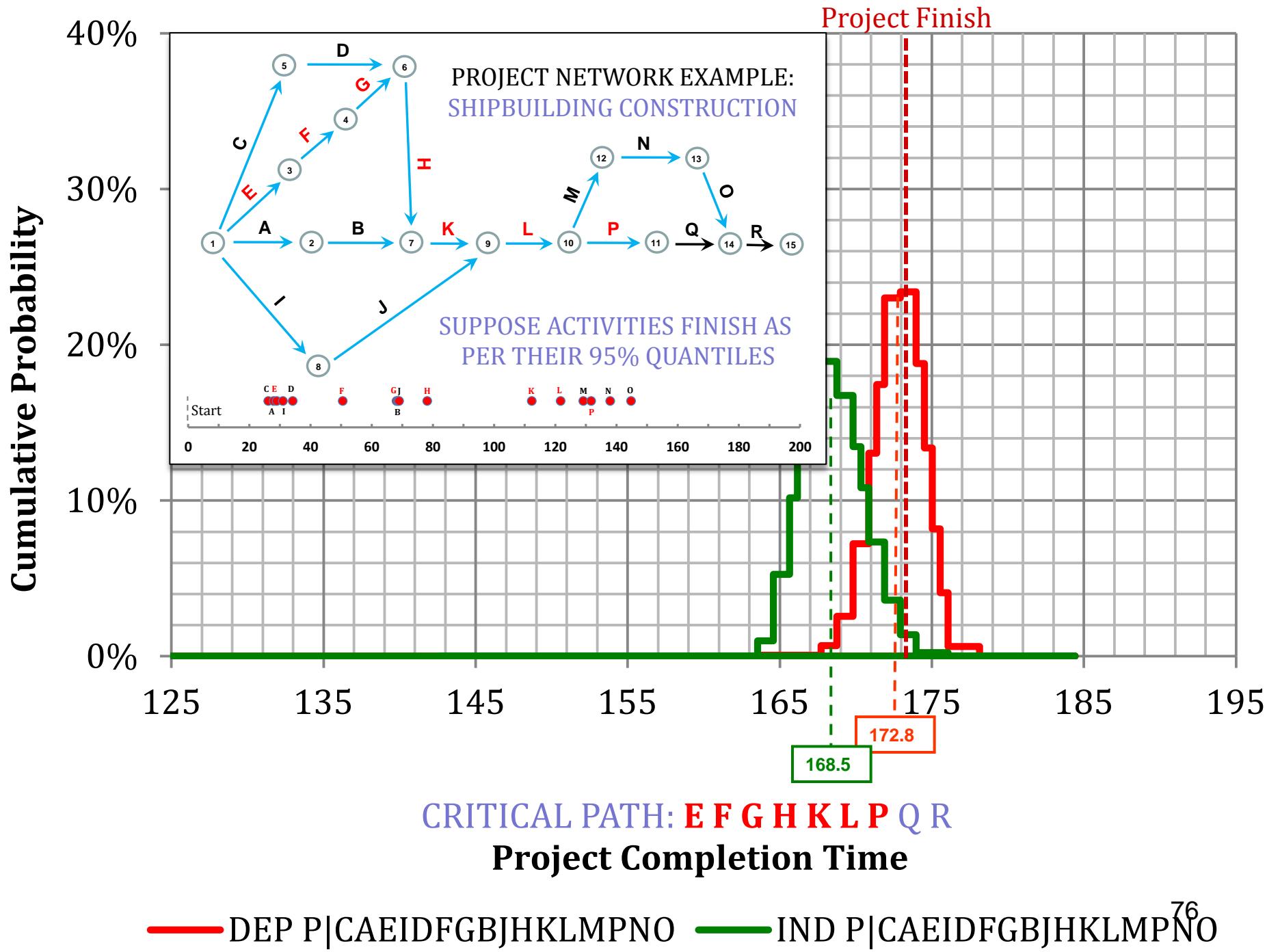


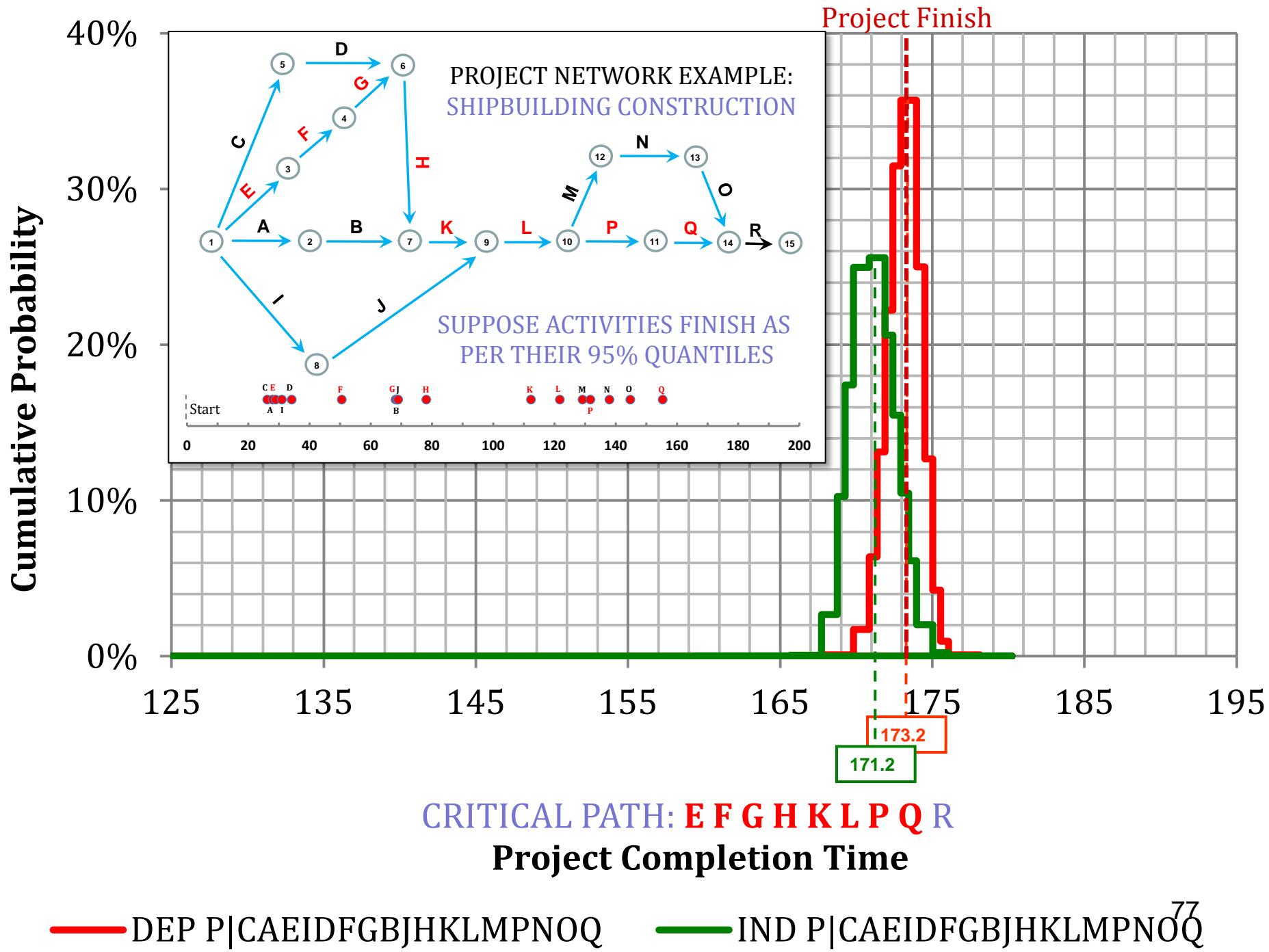


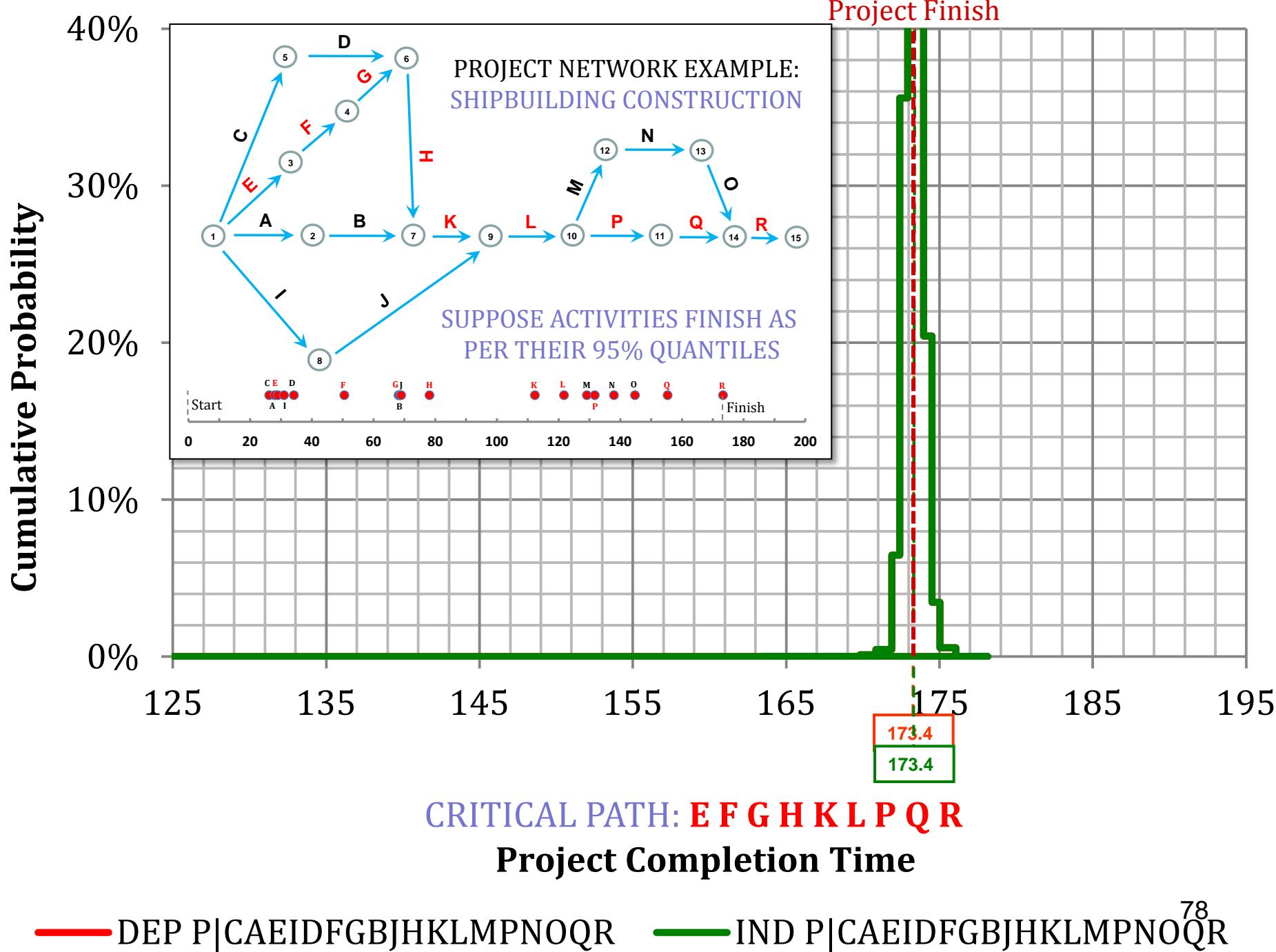












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- Case Study Description
- Bayesian Network Model
- Statistical Dependence Elicitation
- Uncertainty (n) and Dependence (β) Parameter Selection
- Prior Completion Time Uncertainty
- Posterior Analysis: Monitoring Uncertainty
- Conclusion

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Conclusion

1. Accounting for statistical dependence amongst activities results **a priori** in larger uncertainty bands for the project completion time - **Nothing new here!**
2. As activities complete using the Bayes Network analysis the remaining activity completion uncertainty distributions are updated (as if they were known at the start of the project)
3. The speed of learning about the project completion time is enhanced by modeling the activity statistical dependence using a Bayes Network.
4. In case study one third into the project (i.e. **a posteriori**) uncertainty bands are less taking into account activity statistical dependence.
5. The propagation of the completed activities together with updating remaining activity uncertainty distributions through the project and Bayes network structure allows for **more timely corrective actions** from a project management perspective avoiding:

Potential Surprises!!!

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QUESTIONS?

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