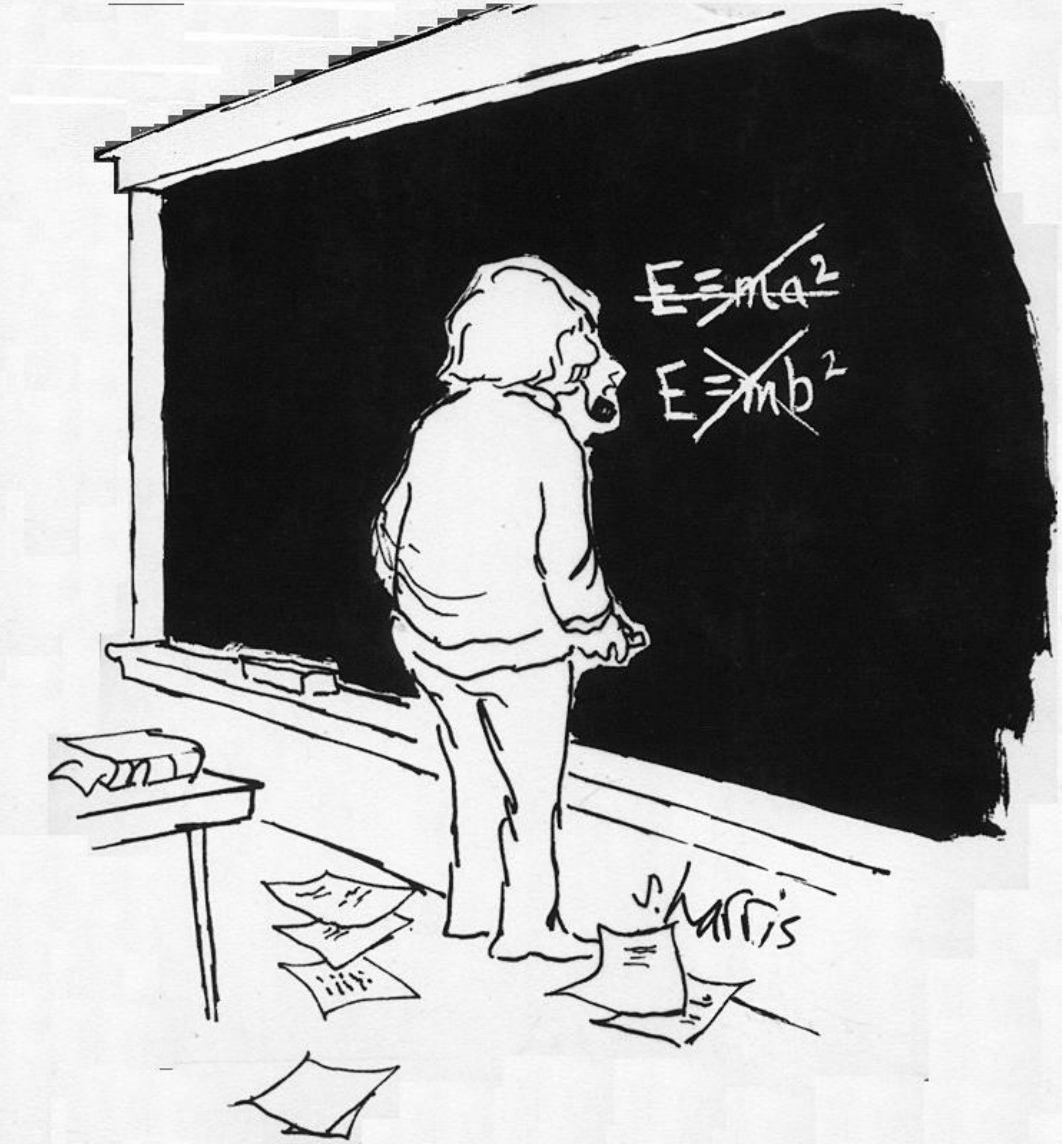

$\cancel{E=ma^2}$
$\cancel{E=mb^2}$
S. Harris

Scientific Creativity as a Combinatorial Process

The Chance Baseline

Goal

- Formulate a theory of scientific creativity
  - that uses
    - Parsimonious assumptions and
    - Logical derivations
  - to obtain
    - Comprehensive explanations and
    - Precise predictions
  - with respect to the most secure empirical results
- In other words, getting the most with the least

Argument: Part One

- Combinatorial models
  - currently get the most with the least relative to any alternative theory.
    - That is, such models
    - make the fewest assumptions,
    - and by logical inferences
    - explain the widest range of established facts
    - and make the most precise predictions with respect to those data

Argument: Part Two

- Even if combinatorial models are incomplete from the standpoint of one or more criteria,
- such models must still provide the baseline for comparing all alternative theories.
- That is, rival theories must account for whatever cannot be accounted for by chance alone, or what exceeds the chance baseline (cf. “null” hypothesis; research on the “hot hand” or parapsychology; etc.)

Creativity in Science: Two Critical Research Sites

- Scientific Careers:
  - Publications
- Scientific Communities:
  - Multiples

Publications

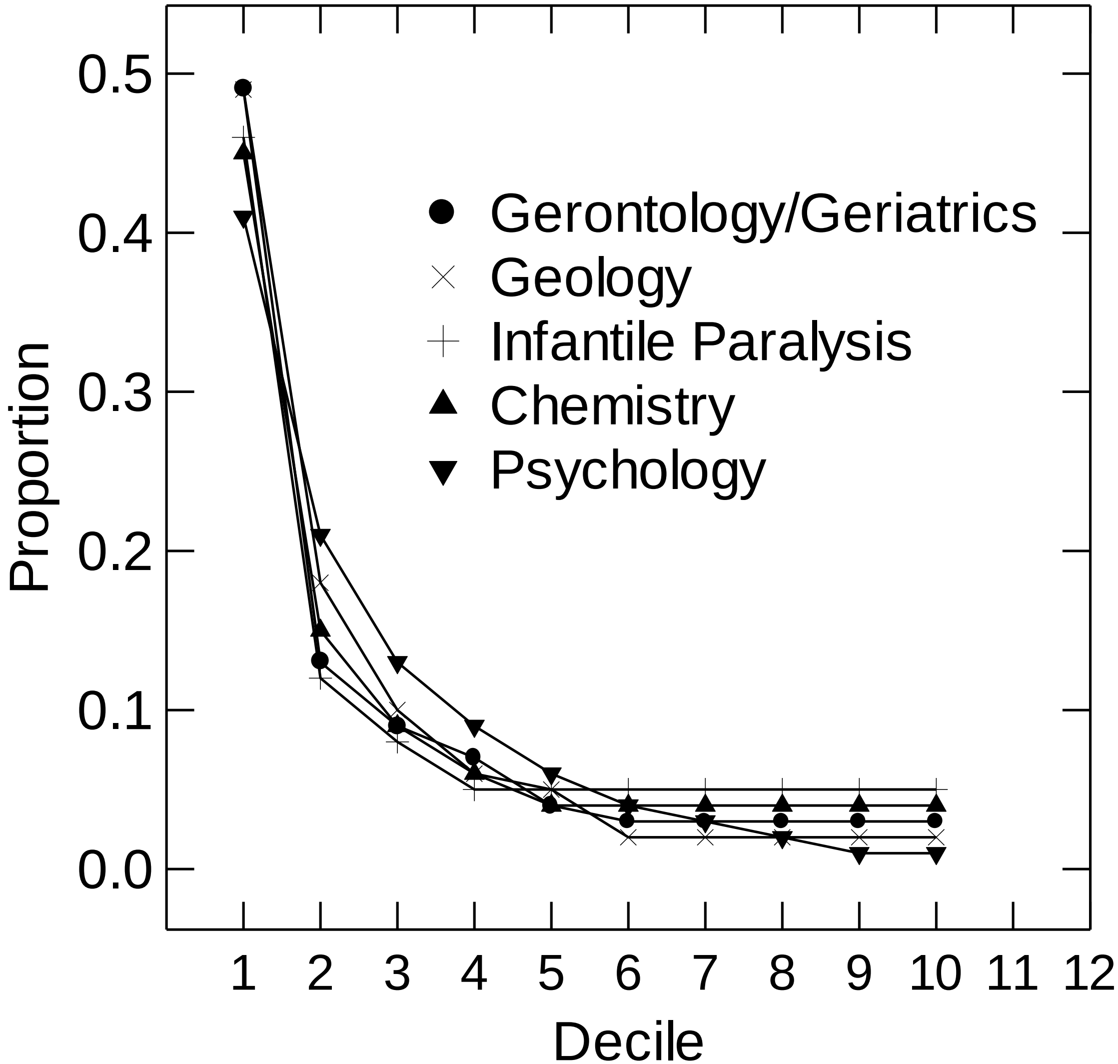
- Individual Variation
- Longitudinal Change

Individual Variation

- Skewed Cross-sectional Distribution

Individual Variation

- Skewed Cross-sectional Distribution
  - 10% $\rightarrow$ 50% / 50% $\rightarrow$ 15%



Gerontology/Geriatrics
Geology
Infantile Paralysis
Chemistry
Psychology
Proportion
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6
7
8
9
10
11
12
Decile

Individual Variation

- Skewed Cross-sectional Distribution
  - Lotka’s Law

Individual Variation

- Skewed Cross-sectional Distribution
  - Lotka's Law:
    - $f\ (T) = k\ T^{-2}$ or $\log\ f\ (T) = \log k - 2 \log T$

Individual Variation

- Skewed Cross-sectional Distribution
  - Lotka's Law:
    - $f\,(T) = k\,T^{-2}$ or $\log\; f\,(T) = \log k - 2 \log T$
    - where T is total lifetime output

Individual Variation

- Skewed Cross-sectional Distribution
  - Lotka’s Law:
  - Price’s Law:
    - $N^{1/2} \longrightarrow$ 50% of total field output

Individual Variation

- Skewed Cross-sectional Distribution
  - Lotka's Law:
  - Price's Law:
    - $N^{1/2} \rightarrow$ 50% of total field output
    - where N is size of field

Individual Variation

- Skewed Cross-sectional Distribution
- Quantity-Quality Relation

Individual Variation

- Skewed Cross-sectional Distribution
- Quantity-Quality Relation
  - Equal-Odds Baseline: $H_i = \rho_1 T_i + u_i$

Individual Variation

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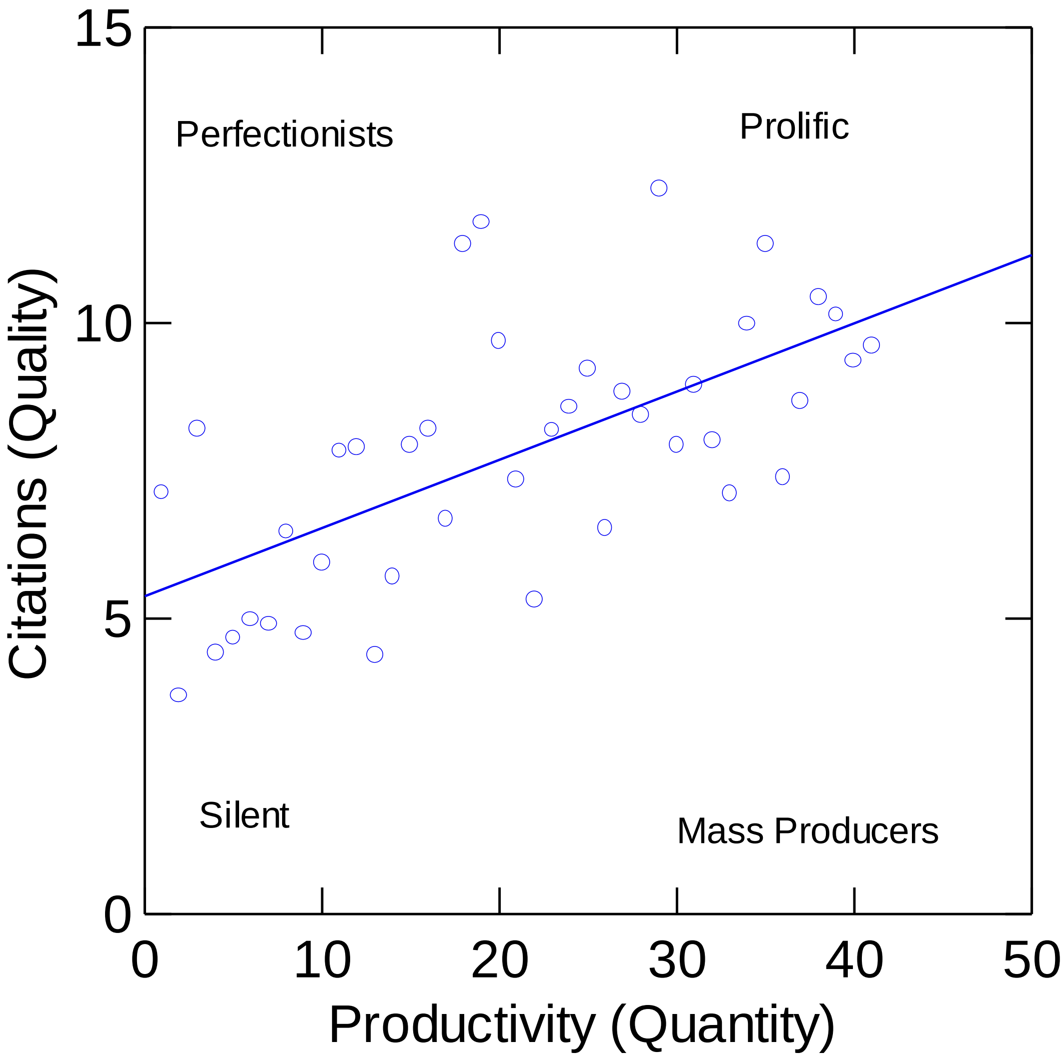
  - where ρ_1 is the overall "hit rate" $(0 < \rho_1 < 1)$ for individuals in a given domain

Individual Variation

- Skewed Cross-sectional Distribution
- Quantity-Quality Relation
  - Equal-Odds Baseline: $H_i = \rho_1 T_i + u_i$
  - where ρ_1 is the overall "hit rate" ($0 < \rho_1 < 1$) for individuals in a given domain,
  - H_i is the number of "hits" (e.g., high-impact publications) for individual *i*, and
  - the random shock $0 \leq u_i \leq T_i (1 - \rho_1)$


Perfectionists
Prolific
Silent
Mass Producers
Citations (Quality)
Productivity (Quantity)
0
5
10
15
0
10
20
30
40
50

Individual Variation

- Skewed Cross-sectional Distribution
- Quantity-Quality Relation
  - Equal-Odds Baseline: $H_i = \rho_1 T_i + u_i$
  - where ρ_1 is the overall “hit rate” ($0 < \rho_1 < 1$) for individuals in a given domain,
  - H_i is the number of “hits” (e.g., high-impact publications) for individual *I*, and
  - the random shock $0 \leq u_i \leq T_i (1 - \rho_1)$
  - N.B.: If ρ_1 were a linear function of T_i, then the overall function would be quadratic, not linear

Longitudinal Change

- Randomness of Annual Output
  - No “runs”
  - Poisson Distribution
    - $P\,(j) = \mu^{j} e^{-\mu} / j!$
    - $e = 2.718\ldots$ and $j! = 1 \times 2 \times 3 \times \ldots \times j$

Representative Productivity Distributions for 10 Hypothetical Scientists

	Career year																			
Scientist	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1	1	0	2	2	1	3	2	0	1	0	3	0	1	2	1	1	0	2	2
2	2	2	0	1	1	2	0	1	2	0	1	2	3	2	1	1	1	2	0	1
3	2	1	1	0	2	0	1	3	0	2	1	2	1	1	2	1	2	2	1	0
4	0	1	2	0	2	0	1	3	1	4	0	0	2	1	1	1	1	2	1	2
5	2	1	0	1	0	1	1	3	2	1	1	2	3	2	1	1	2	1	0	0
6	0	0	1	1	2	1	2	1	2	0	1	1	2	0	1	3	2	2	2	1
7	2	2	0	1	2	0	1	1	2	3	1	2	0	3	1	2	1	0	1	0
8	1	2	0	2	2	1	3	0	1	1	3	2	1	0	0	1	0	1	2	2
9	2	1	0	2	1	1	2	4	0	0	2	1	3	0	1	1	0	2	1	1
10	1	1	2	1	2	1	0	3	2	1	1	1	2	3	2	1	0	0	1	0

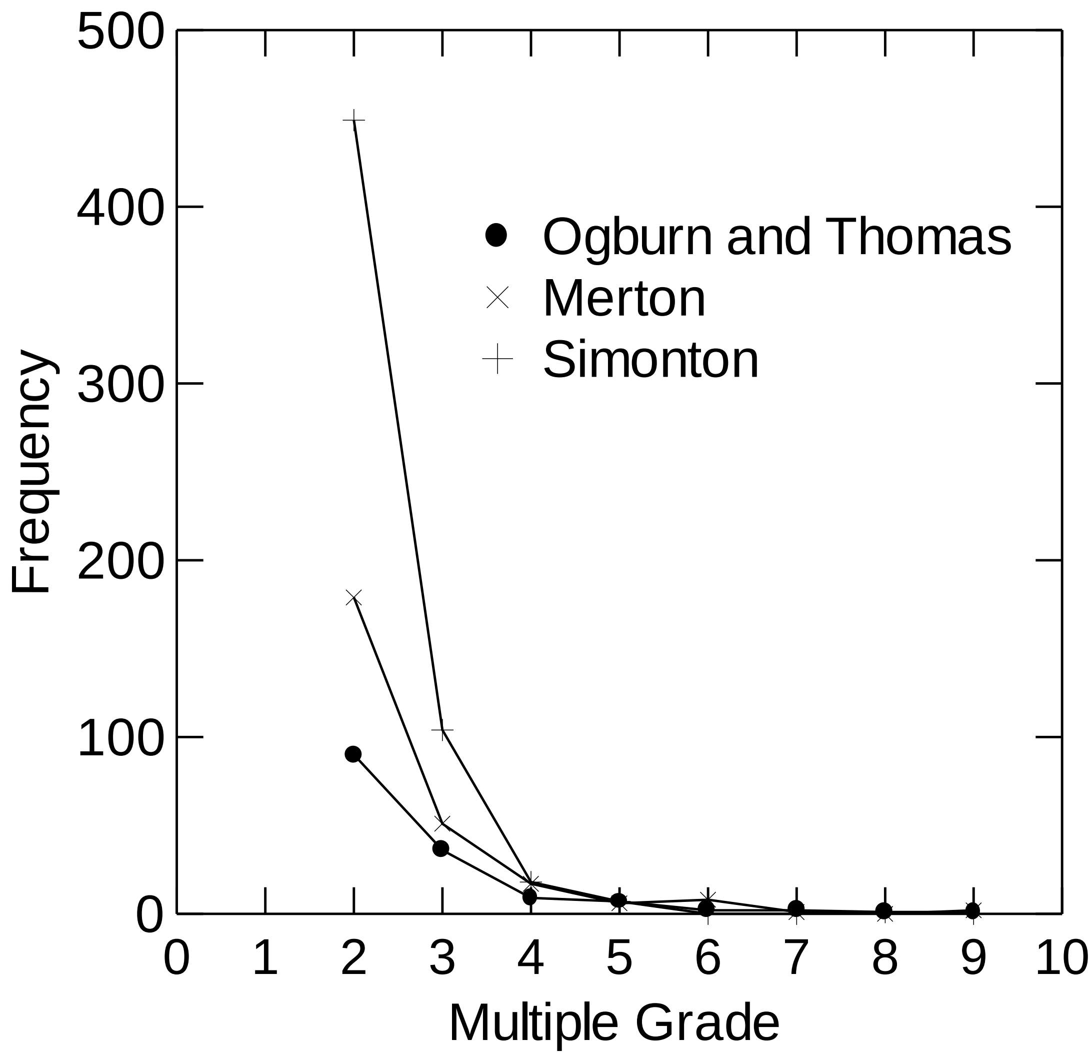
Note. Each scientist is presumed to produce 25 contributions randomly distributed over 20 career years, with a Poisson distribution for the number contributions per yearly unit (where $\mu = 1.25$).

Longitudinal Change

- Randomness of Annual Output
- Quantity-Quality Relation
  - Random Fluctuation around a Quality Ratio Baseline
  - Hence, the Equal-Odds Baseline:
  - $H_{it} = \rho_2 T_{it} + u_{it}$ ($\rho_2 = \rho_1$ if estimated from the same cross-sectional sample)
  - for the *i*th individual in career year *t*,
  - and where $0 \leq u_{it} \leq T_{it} (1 - \rho_2)$

Multiples

- Distribution of Multiple Grades



500
400
300
200
100
0
Frequency
0
1
2
3
4
5
6
7
8
9
10
Multiple Grade
Ogburn and Thomas
Merton
Simonton

Multiples

- Distribution of Multiple Grades
- Temporal Separation of Multiple Discoveries

Multiples

- Distribution of Multiple Grades
- Temporal Separation of Multiple Discoveries
- Individual Variation in Multiple Participation

Multiples

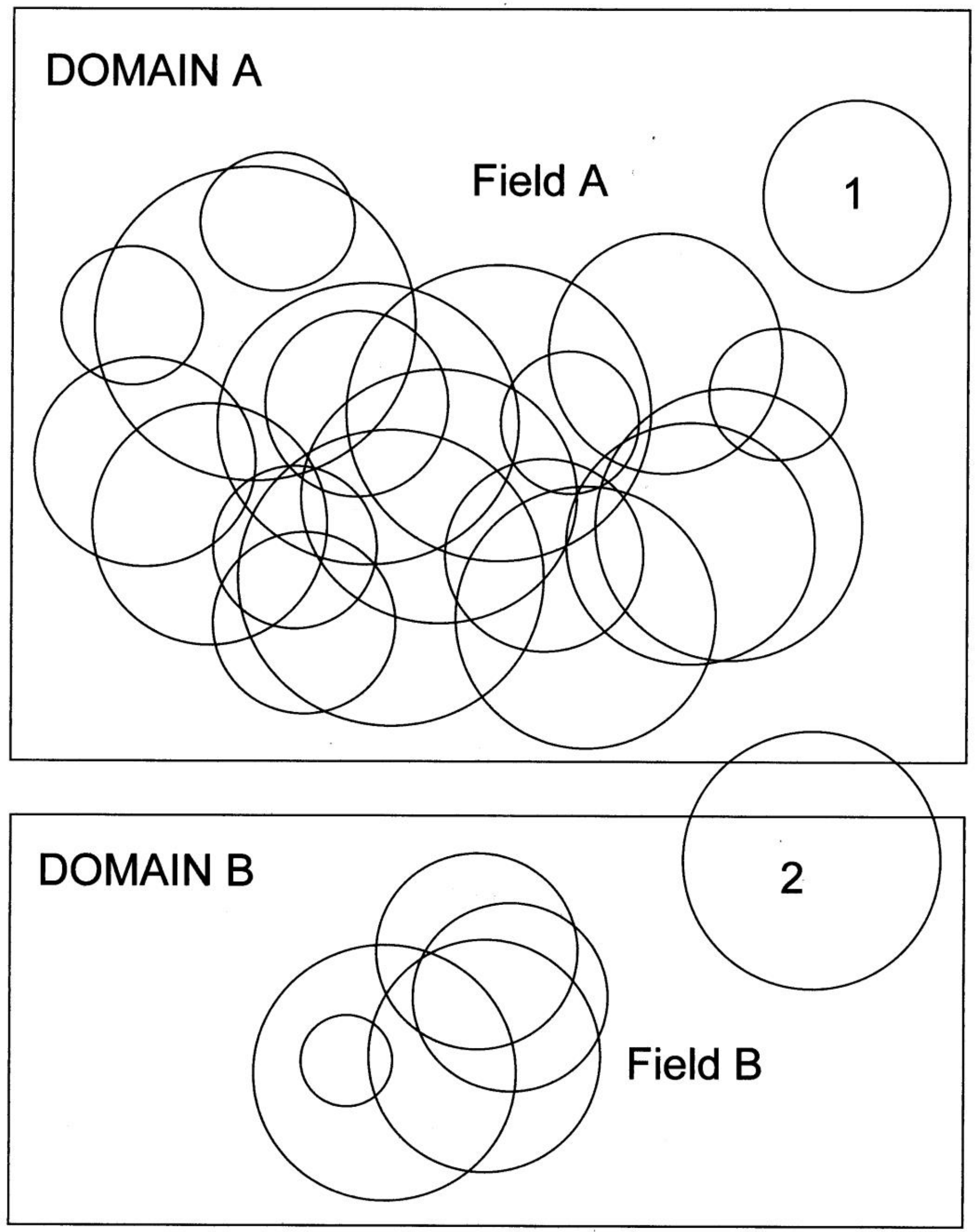
- Distribution of Multiple Grades
- Temporal Separation of Multiple Discoveries
- Individual Variation in Multiple Participation
- Degree of Multiple Identity

Combinatorial Processes

- Definitions
- Assumptions
- Implications
- Elaboration
- Integration

Definitions

- Individual
- Domain
- Field

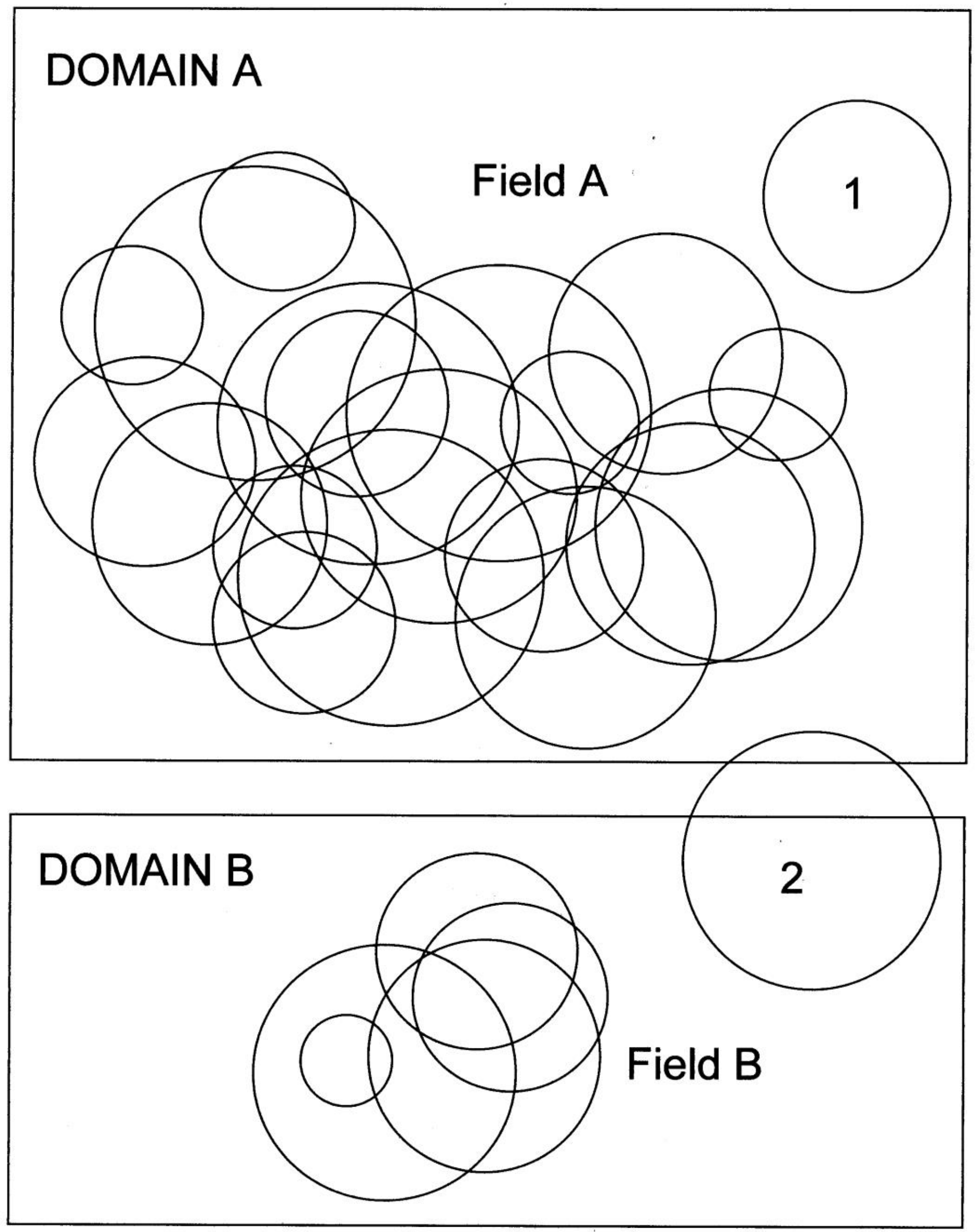

DOMAIN A
Field A
1
2
DOMAIN B
Field B

Assumptions

- Individual Samples from Domain Ideas

Assumptions

- Individual Samples from Domain Ideas
  - Assume samples random or quasi-random

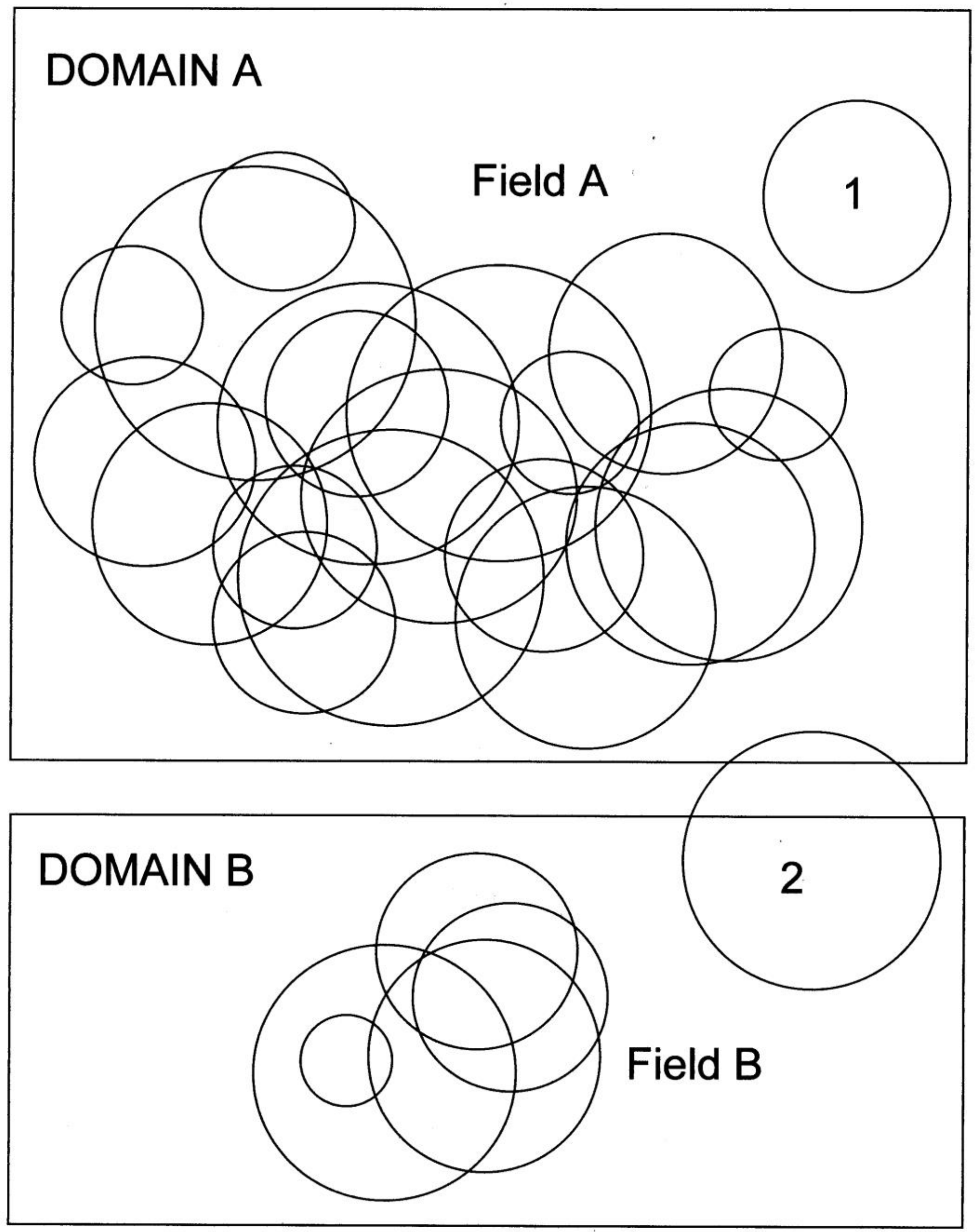

DOMAIN A
Field A
1
DOMAIN B
2
Field B

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
  - Postulate a normal distribution


DOMAIN A
Field A
1
2
DOMAIN B
Field B

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas
  - Variable degrees of constraint depending on nature of domain
    - Scientific revolutionaries vs. normal scientists
    - Paradigmatic vs. nonparadigmatic scientists
    - Scientists vs. artists

Assumptions

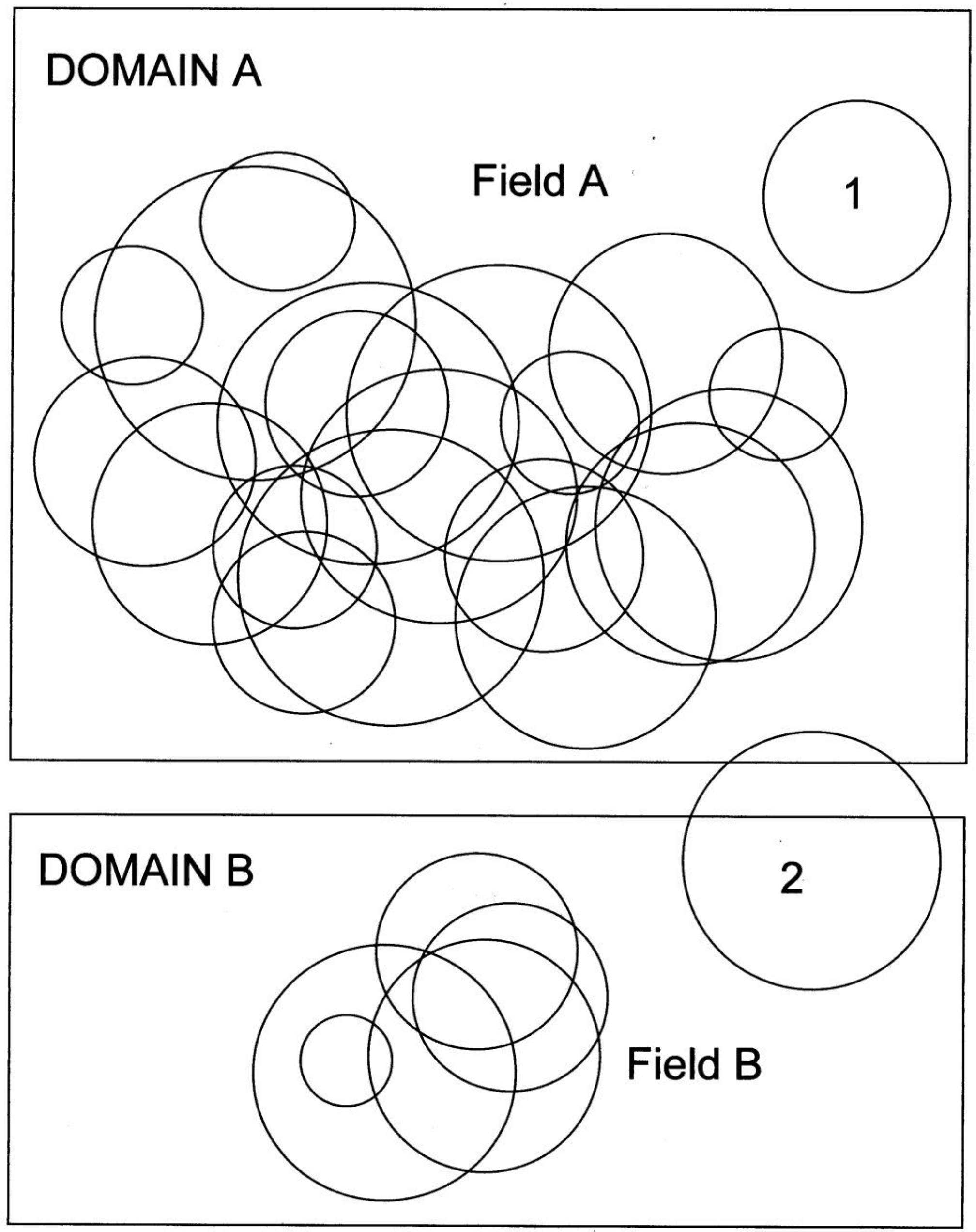
- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas
- Variation in Quality of Combinations

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas
- Variation in Quality of Combinations
  - Differential fitness with respect to scientific criteria (facts, logic, etc.)
  - Small proportion publishable, an even smaller proportion high impact

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas
- Variation in Quality of Combinations
- Variation in Size of Fields

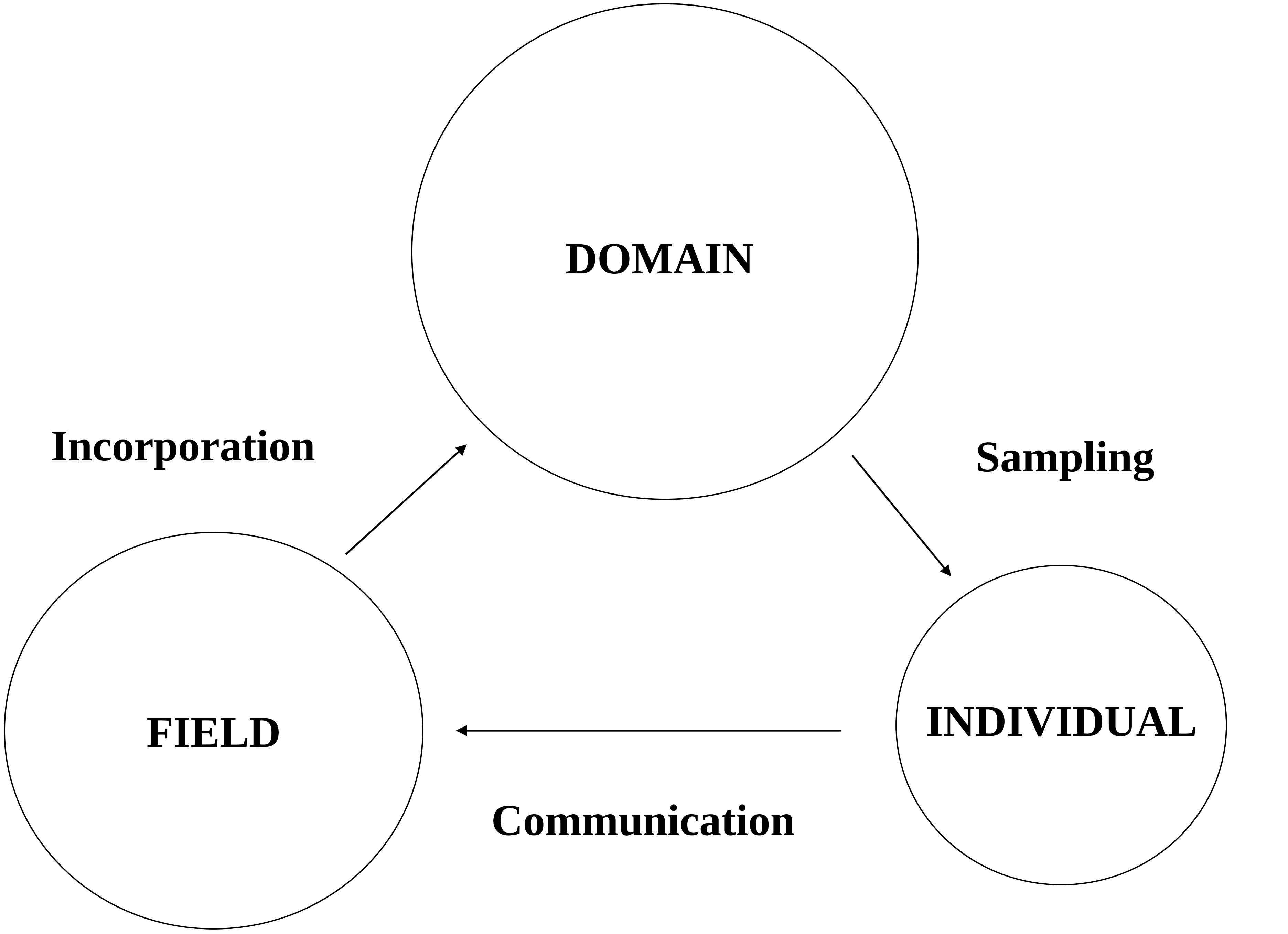

DOMAIN A
Field A
1
DOMAIN B
2
Field B

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas
- Variation in Quality of Combinations
- Variation in Size of Fields
- Communication of Ideational Combinations

Assumptions

- Individual Samples from Domain Ideas
- Within-Field Variation in Sample Size
- Quasi-Random Combination of Ideas
- Variation in Quality of Combinations
- Variation in Size of Fields
- Communication of Ideational Combinations
  – If accepted, then incorporation into the domain pool, completing the cycle


DOMAIN
Incorporation
Sampling
FIELD
INDIVIDUAL
Communication

Communication-Incorporation:

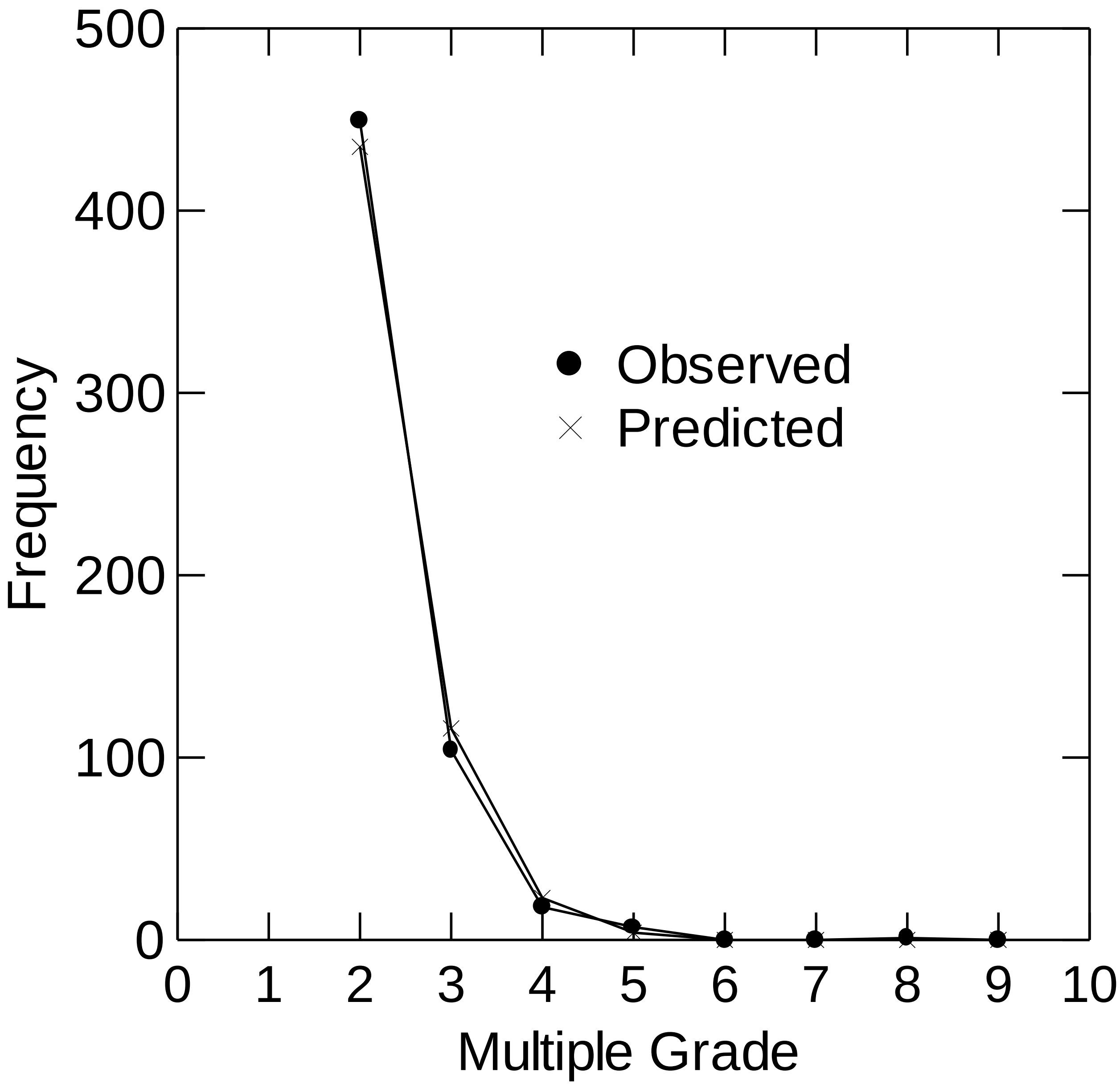
- Rate increases with speed of
  - Communication practices (journals vs. books; least-publishable units)
  - Gate-keeping procedures (peer review; editorial policies)
  - Publication lags (1st- vs. 2nd-tier journals)
  - Diffusion to secondary sources (introductory texts, popularizations, etc.)
- Hence, variation across time and discipline

Implications

- Research Publications
  - – Cross-sectional Variation
  - – Longitudinal Change

Implications

- Multiple Discoveries
  - Multiple Grades



Frequency
500
400
300
200
100
0
0 1 2 3 4 5 6 7 8 9 10
Multiple Grade
Observed
Predicted

Implications

- Multiple Discoveries
  - Multiple Grades
    - Variation across time and discipline
  - Temporal Separation
    - Variation across time and discipline

Implications

- Multiple Discoveries
  - Multiple Grades
  - Temporal Separation
  - Multiples Participation

Implications

- Multiple Discoveries
  - Multiple Grades
  - Temporal Separation
  - Multiples Participation
    - Number of ideational combinations
    - Number of overlapping domain samples

Implications

- Multiple Discoveries
  - Multiple Grades
  - Temporal Separation
  - Multiples Participation
  - Multiple Identity

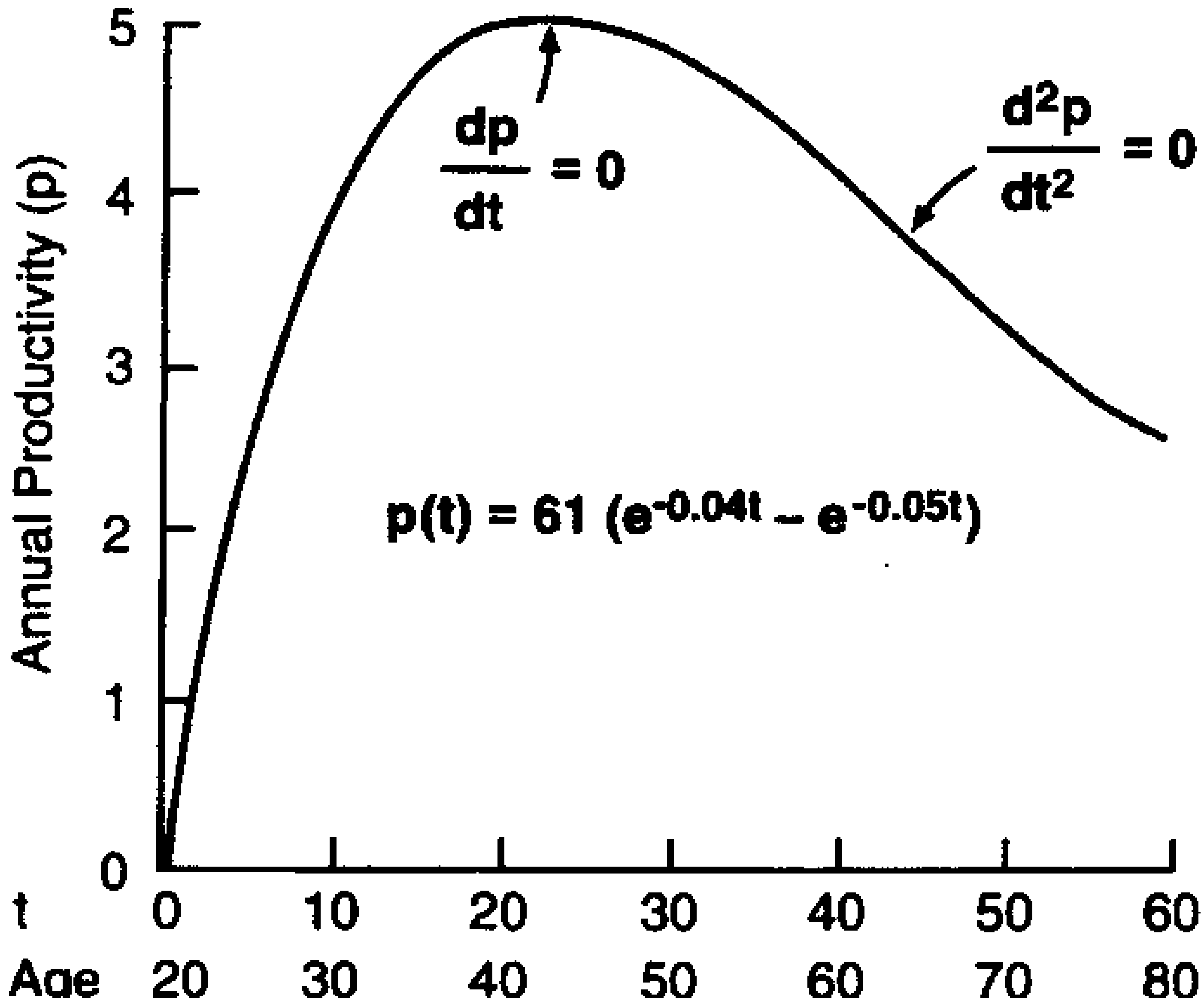
Elaboration

- Aggregated Data on Career Output
  - Aggregated Across Time Units
  - Aggregated Across Scientists
- Cognitive Combinatorial Model
  - Two-step process
    - Ideation generates combinations
    - Elaboration generates communications
  - Individual differences in
    - Domain sample
    - Career onset

- $p(t) = abm(b - a)^{-1}(e^{-at} - e^{-bt})$
  - where $p(t)$ is ideational output at career age t (in years),
  - e is the exponential constant (~ 2.718),
  - a the typical ideation rate for the domain ($0 < a < 1$),
  - b the typical elaboration rate for the domain ($0 < b < 1$),
  - m the individual's *creative potential* (i.e. maximum number of ideational combinations in indefinite lifetime).
- If $a = b$, then $p(t) = a^2mte^{-at}$
- Number of communications T_{it} is proportional to p.
- Individual differences in
  - Creative potential (m)
  - Age at career onset (i.e., chronological age at $t = 0$)

Implications

- Typical Career Trajectories



Annual Productivity (p)
5
4
3
2
1
0
t
0
10
20
30
40
50
60
Age
20
30
40
50
60
70
80
$\frac{dp}{dt} = 0$
$\frac{d^2p}{dt^2} = 0$
$p(t) = 61\,(e^{-0.04t} - e^{-0.05t})$

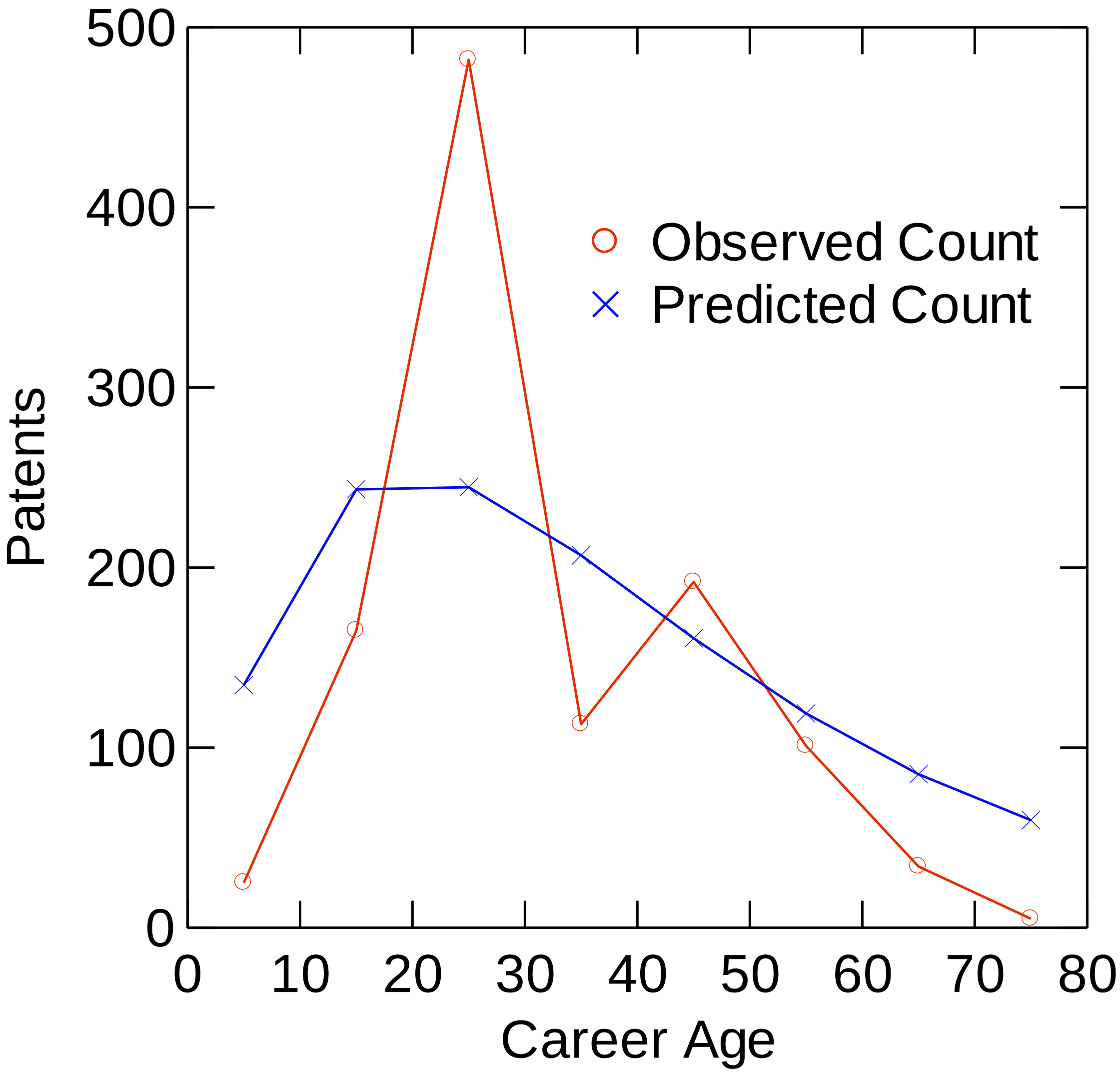
N.B.

- The above curve has been shown to correlate in the mid- to upper-.90s for numerous data sets in which output information has been aggregated across many individual careers
- Yet even in the case of highly productive individuals, the predicted curve does reasonably well

e.g., the career of Thomas Edison

$$C_{Edison}(t) = 2595(e^{-.044t} - e^{-.058t})$$

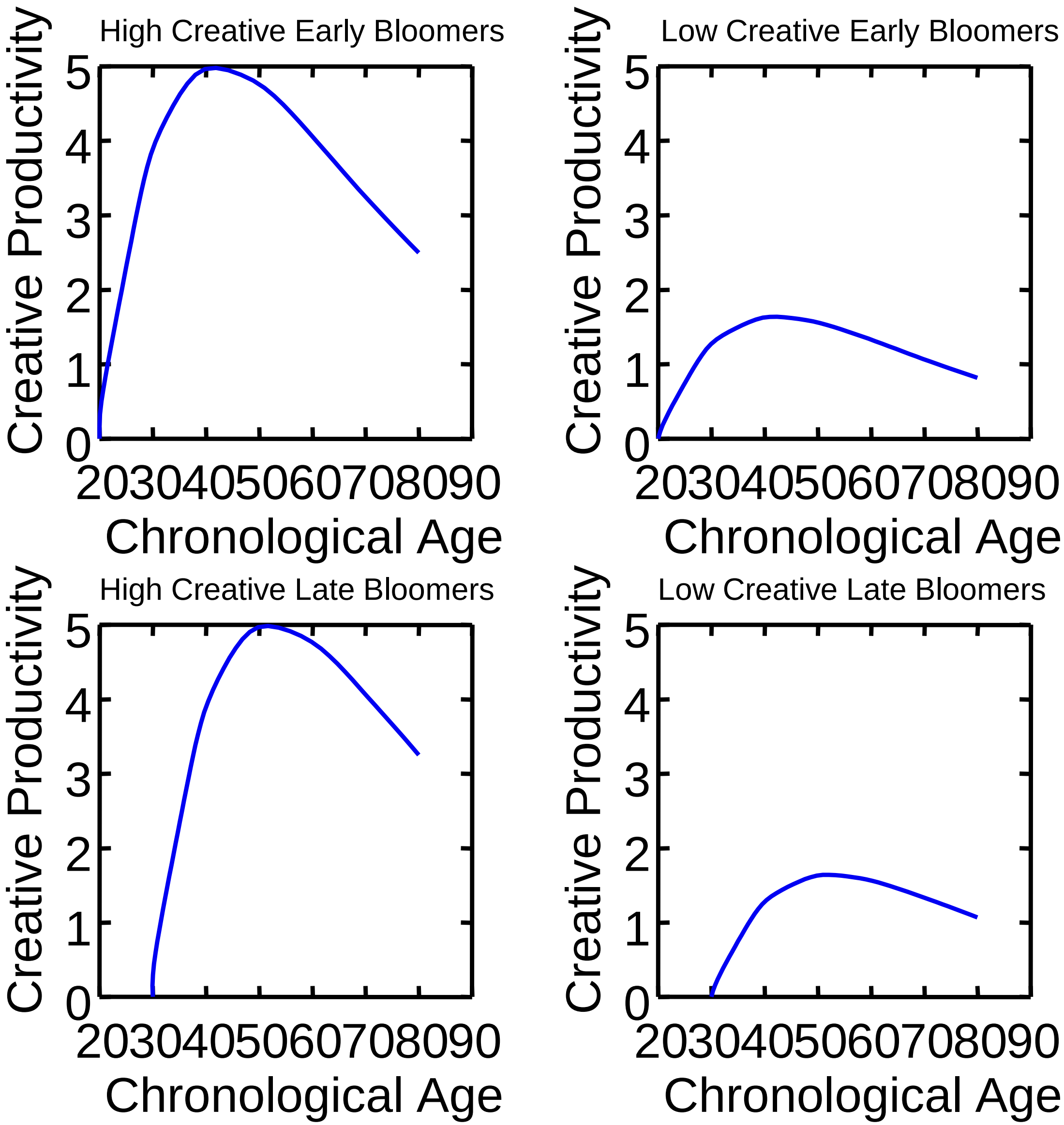
$$r = .74$$



Observed Count
Predicted Count
Patents
Career Age
0
100
200
300
400
500
0
10
20
30
40
50
60
70
80

Implications

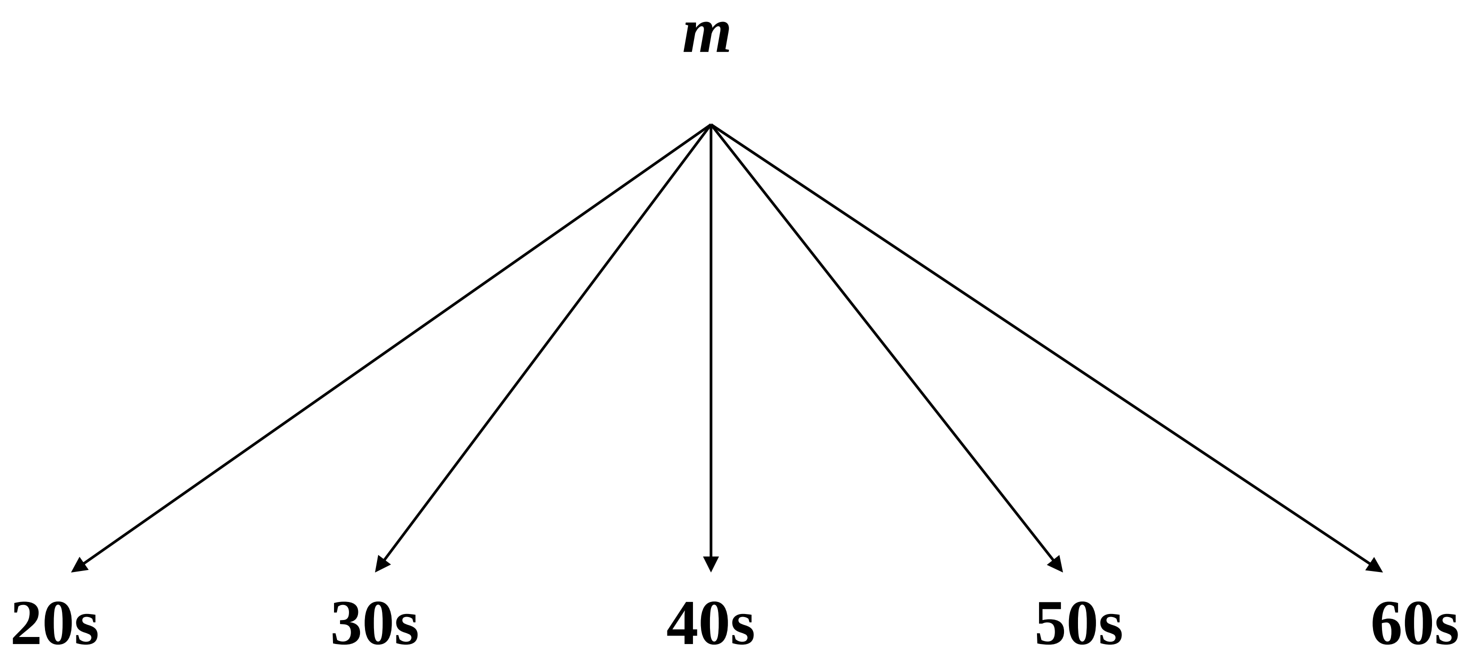
- Typical Career Trajectories
- Individual Differences in Trajectories
  - Fourfold Typology
    - High versus Low Creative Potential
    - Early versus Late Age at Career Onset


High Creative Early Bloomers
Low Creative Early Bloomers
High Creative Late Bloomers
Low Creative Late Bloomers
Creative Productivity
Chronological Age
0
1
2
3
4
5
20
30
40
50
60
70
80
90

Specific Prediction

- Individual differences in output across consecutive age periods (5- or 10-year units) for scientists with same age at career onset yields a specific pattern of correlations across those units, namely one most consistent with
  - a single-factor model, rather than
  - an autoregressive (simplex or quasi-simplex) model.

Single-Factor Model

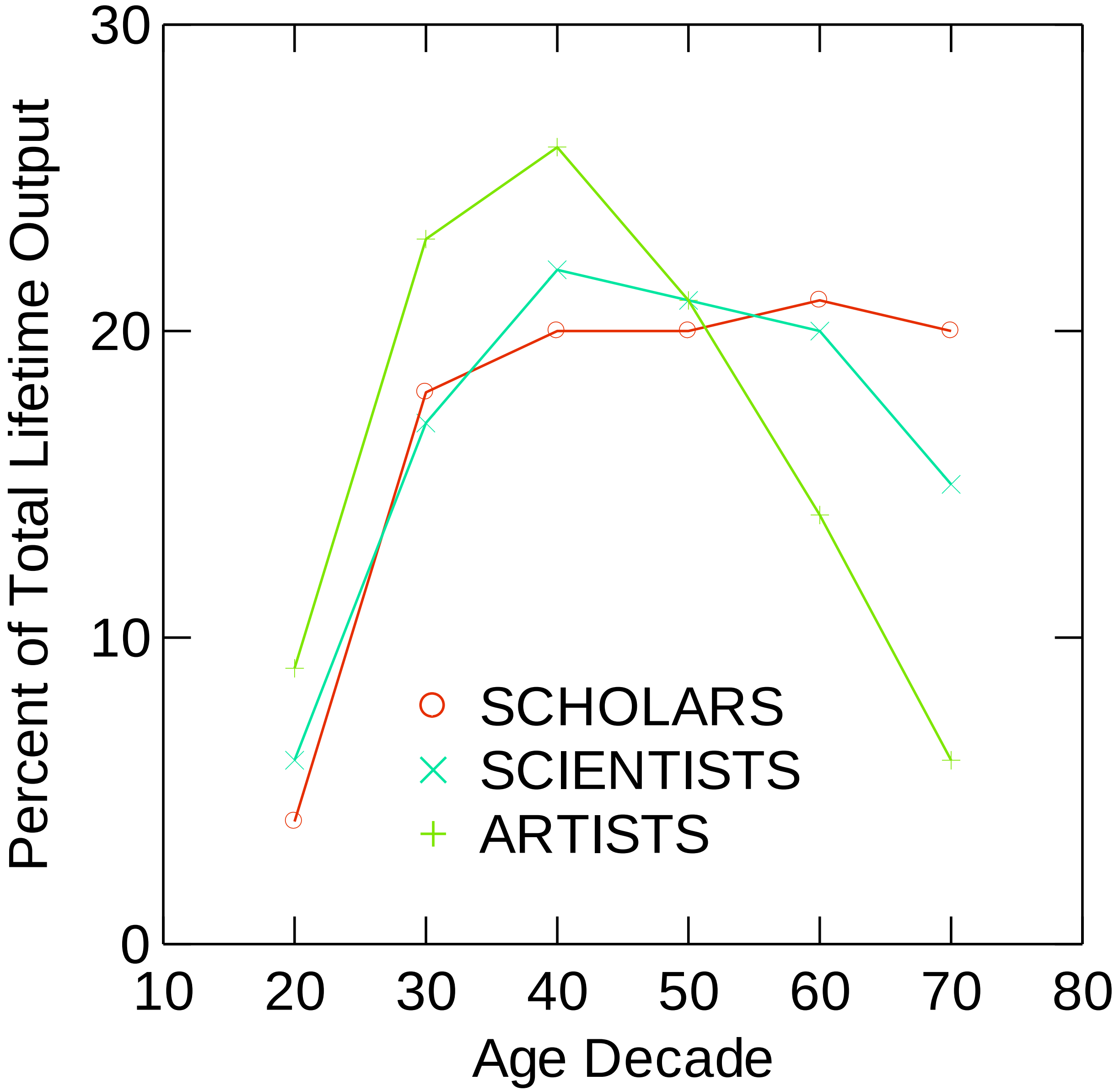


Autoregressive Model

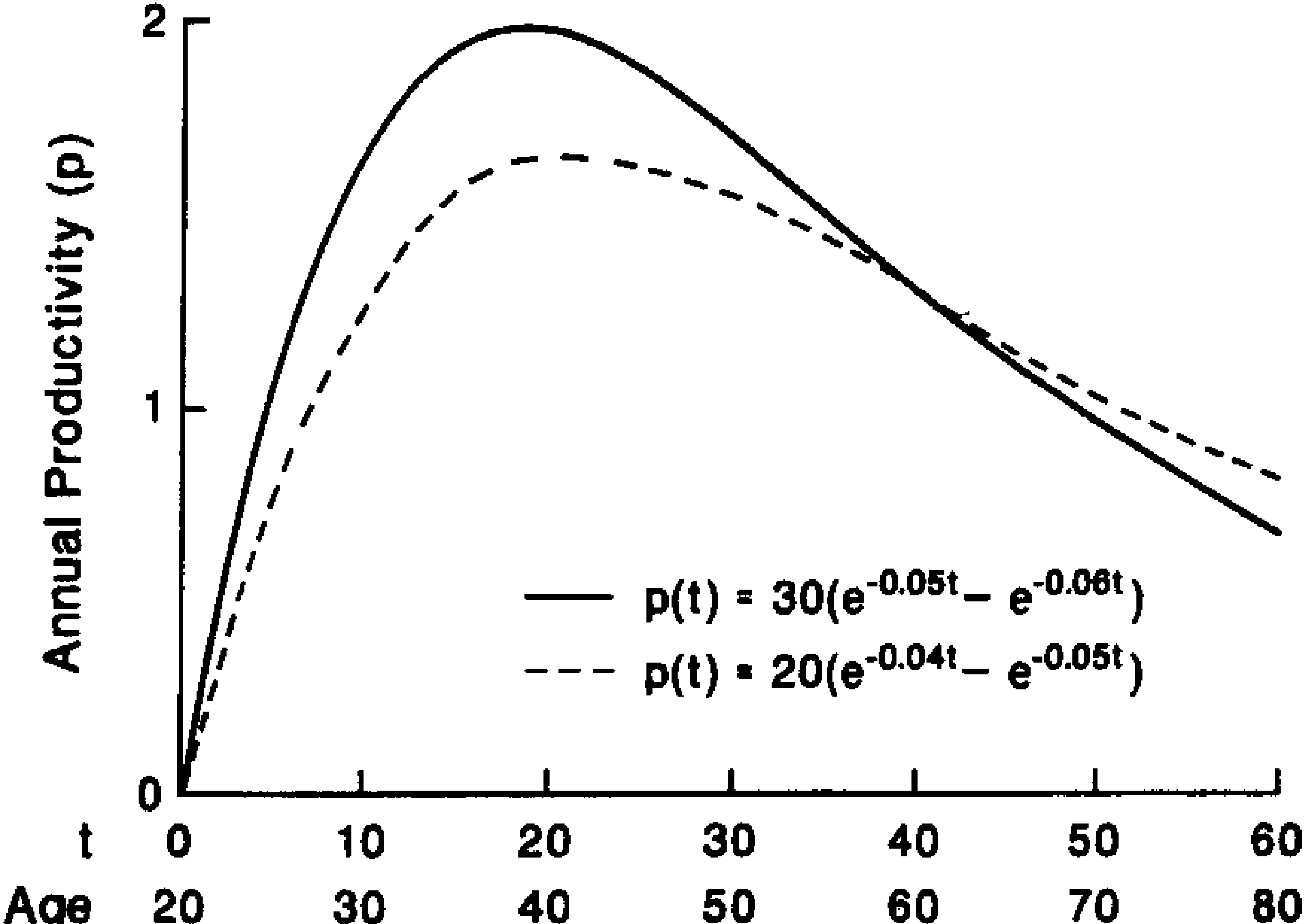
Former single-factor model already confirmed on distinct data sets (e.g., there is no tendency for the correlations between two age periods to decline as a function of the temporal separation between the two periods; i.e., no decline with distance from matrix diagonal)

Implications

- Typical Career Trajectories
- Individual Differences in Trajectories
- Domain Variation in Trajectories



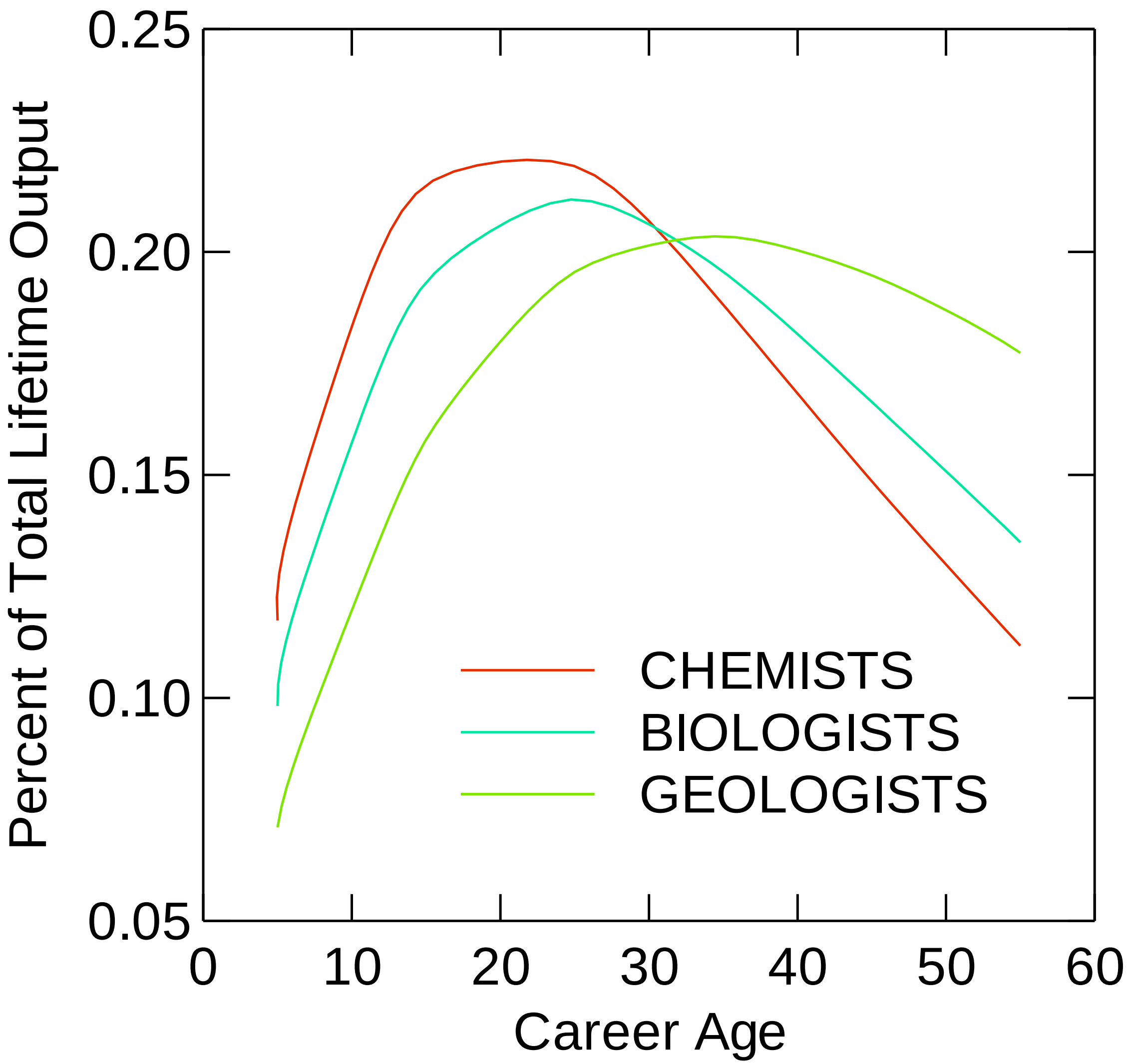
30
20
10
0
10
20
30
40
50
60
70
80
Percent of Total Lifetime Output
Age Decade
SCHOLARS
SCIENTISTS
ARTISTS



Annual Productivity (p)
2
1
0
t
0
10
20
30
40
50
60
Age
20
30
40
50
60
70
80
$p(t) = 30(e^{-0.05t} - e^{-0.06t})$
$p(t) = 20(e^{-0.04t} - e^{-0.05t})$

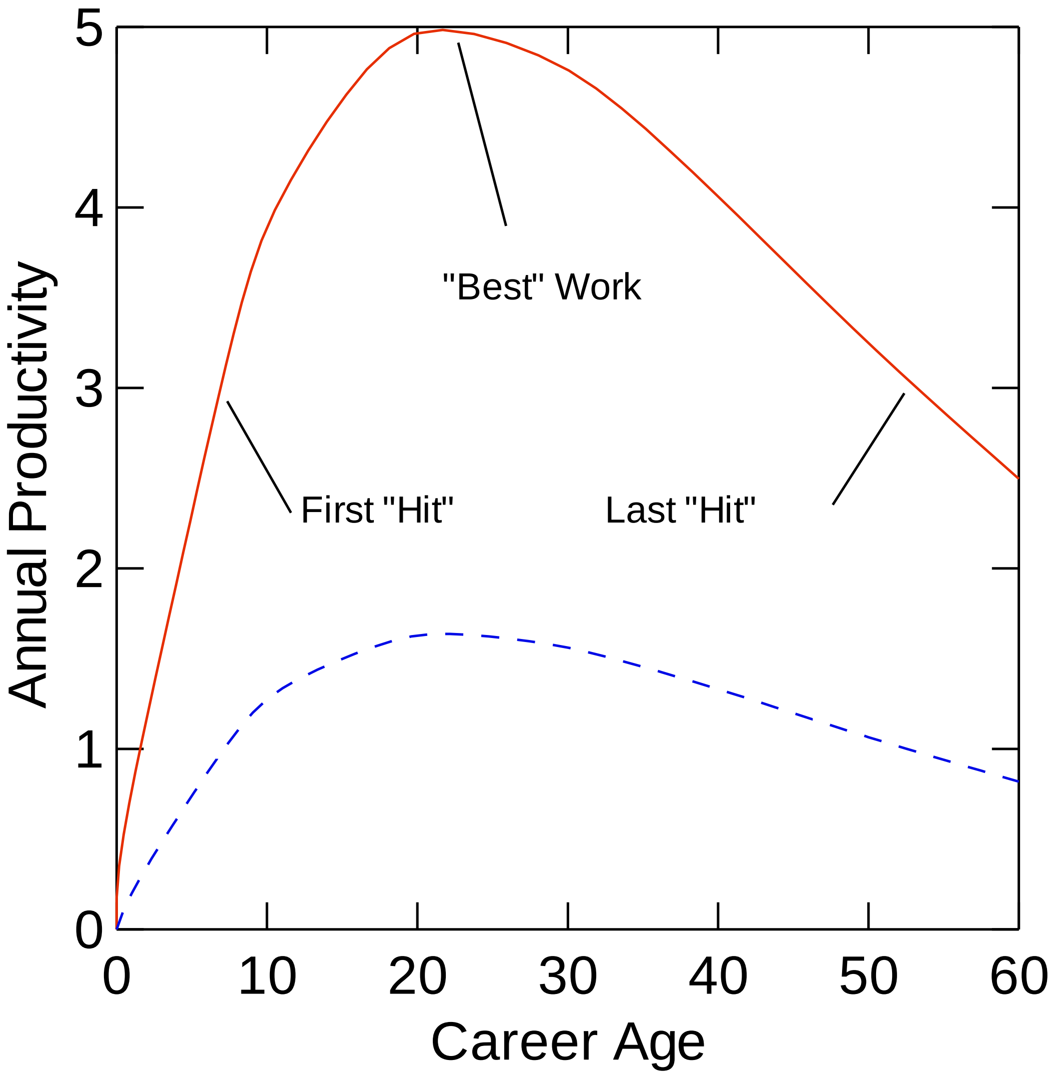
Estimates for Three Disciplines

			Peak Age	*Peak Age*	
Domain	*a*	*b*	*Career*	*Chrono -logical*	*Half-life*
Chemists	.042	.057	20.4	40.4	16.5
Biologists	.033	.052	23.9	43.9	21.0
Geologists	.024	.036	33.8	53.8	28.9

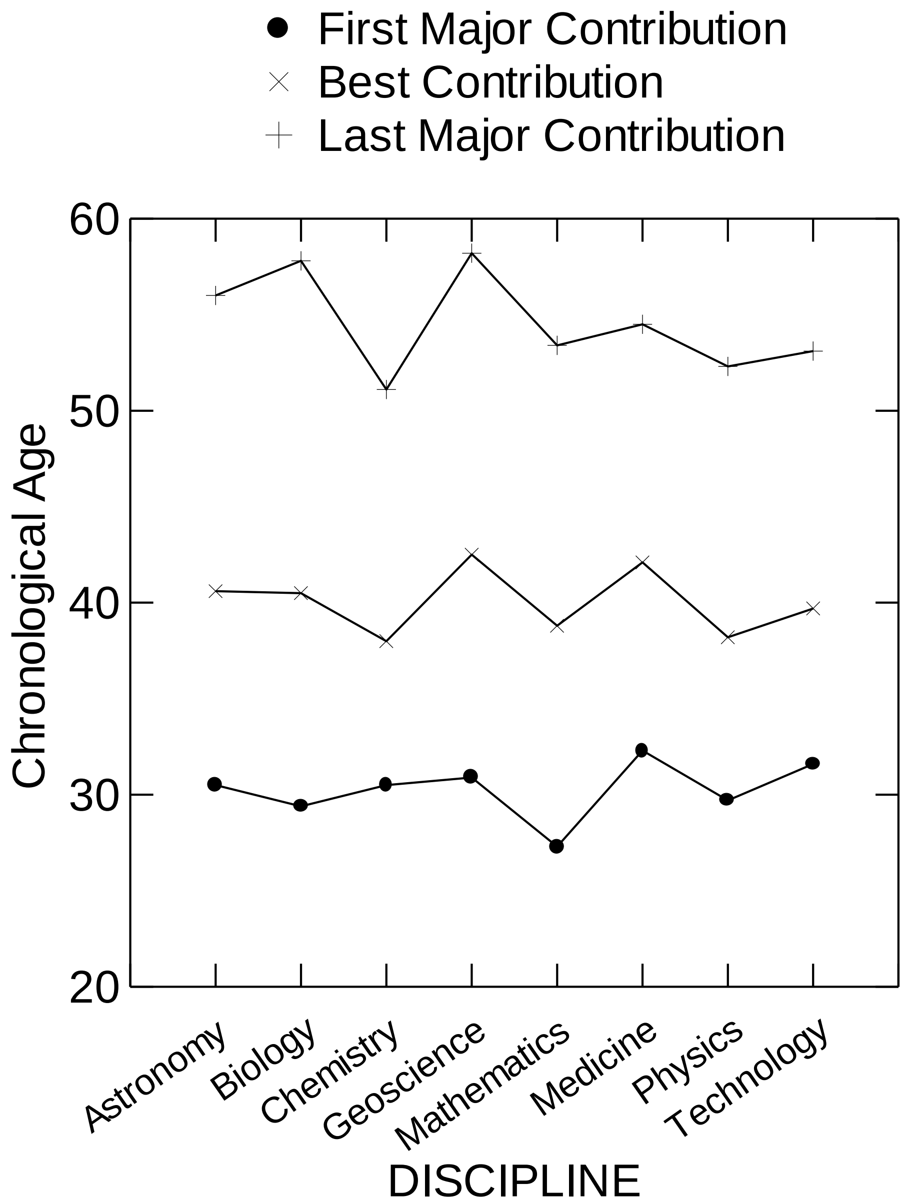

0.25
0.20
0.15
0.10
0.05
0
10
20
30
40
50
60
Career Age
Percent of Total Lifetime Output
CHEMISTS
BIOLOGISTS
GEOLOGISTS

Implications

- Typical Career Trajectories
- Individual Differences in Trajectories
- Domain Variation in Trajectories
- Placement of Career Landmarks
  - Across domains

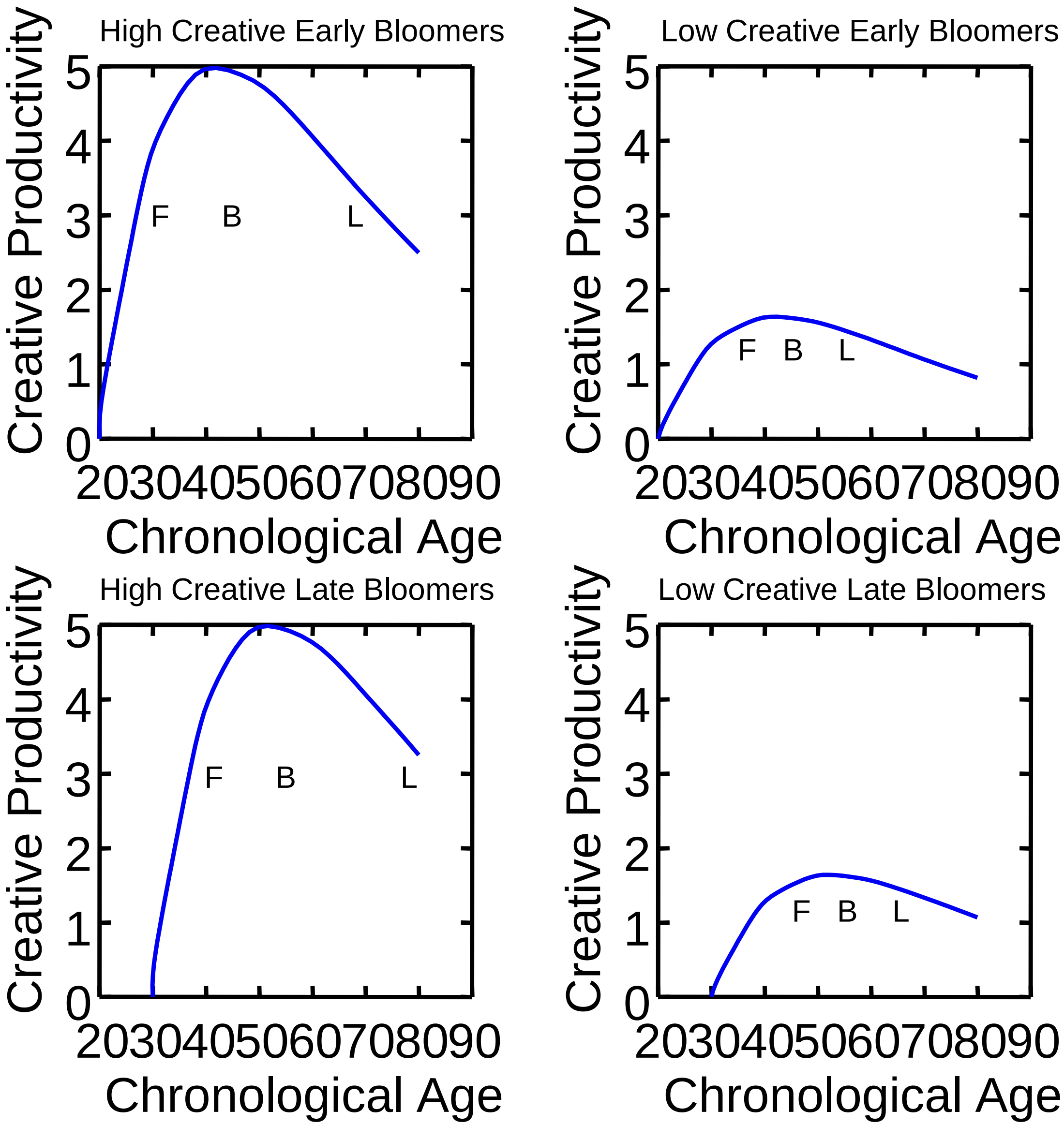


"Best" Work
First "Hit"
Last "Hit"
Annual Productivity
Career Age
0
1
2
3
4
5
0
10
20
30
40
50
60


First Major Contribution
Best Contribution
Last Major Contribution
Chronological Age
60
50
40
30
20
Astronomy
Biology
Chemistry
Geoscience
Mathematics
Medicine
Physics
Technology
DISCIPLINE

Implications

- Typical Career Trajectories
- Individual Differences in Trajectories
- Domain Variation in Trajectories
- Placement of Career Landmarks
  - Across domains
  - Across individuals


High Creative Early Bloomers
Low Creative Early Bloomers
High Creative Late Bloomers
Low Creative Late Bloomers
Creative Productivity
Chronological Age
0
1
2
3
4
5
20
30
40
50
60
70
80
90
F
B
L

Specific Predictions

- Given the above, it is possible to derive predictions regarding the pattern of correlations among
  - the ages of the three career landmarks (*F*, *B*, *L*),
  - the age at maximum output rate (*x*),
  - final lifetime productivity (*T*),
  - the maximum output rate (*X*), and
  - the time lapse or delay (*d*) between career onset and first career landmark (i.e., preparation period)
- In particular …

Specific Predictions

- *1A: Total lifetime productivity correlates*
  - *negatively with the chronological age of the first contribution (*$r_{TF} < 0$*) and*
  - *positively with the chronological age of the last contribution (*$r_{TL} > 0$*) .*

Specific Predictions

- *1B: Maximum output rate correlates*
  - *negatively with the chronological age of the first contribution ($r_{XF} < 0$) and*
  - *positively with the chronological age of the last contribution ($r_{XL} > 0$).*

Specific Predictions

- *2A: Total lifetime productivity correlates*
  - *zero with the chronological age at the maximum output rate (r_{Tx} = 0) and*
  - *zero with the chronological age at the best contribution (r_{TB} = 0).*

Specific Predictions

- *2B: Maximum output rate correlates*
  - *zero with the chronological age at the maximum output rate (*r_{Xx} *= 0) and*
  - *zero with the chronological age at the best contribution (*r_{XB} *= 0).*

Specific Predictions

- *3A: The chronological age at the maximum output rate correlates positively with both*
  - *the chronological age at the first contribution ($r_{xF} > 0$) and*
  - *the chronological age at the last contribution ($r_{xL} > 0$).*

Specific Predictions

- *3B: The chronological age of the best contribution correlates positively with both*
  - *the chronological age at the first contribution* ($r_{FB} > 0$) *and*
  - *the chronological age at the last contribution* ($r_{BL} > 0$).

Specific Predictions

- *4: The first-order partial correlation between the ages of first and last contribution is negative after partialling out either*
  - *the chronological age at the best contribution* ($r_{FL.B} = r_{FL} - r_{FB}r_{LB} < 0$) *or*
  - *the chronological age at the maximum output rate* ($r_{FL.x} = r_{FL} - r_{Fx}r_{Lx} < 0$)

Specific Predictions

- *5: The time interval between the chronological age at career onset and the chronological age at first contribution is negatively correlated with both*
  - *total lifetime productivity* ($r_{Td} < 0$) *and*
  - *the maximum output rate* ($r_{Xd} < 0$).

Discussion

- Foregoing predictions unique to the combinatorial model
  - That is, they cannot be generated by alternative theories (e.g., cumulative advantage, human capital)
- Furthermore, all predictions have been confirmed on several independent data sets

Discussion

- Moreover, if we assume that eminence (E) is highly correlated with lifetime productivity ($r_{ET} >> 0$), then we obtain additional predictions:
- *Eminence correlates*
  - *negatively with the age of the first contribution* ($r_{EF} < 0$),
  - *positively with the age of the last contribution* ($r_{EL} > 0$),
  - *zero with the age at the maximum output rate* ($r_{Ex} = 0$),
  - *zero with the age at the best contribution* ($r_{EB} = 0$), *and*
  - *negatively with the time interval between the age at career onset and the age at first contribution* ($r_{Ed} < 0$)
- These predictions also empirically confirmed

Integration: Combinatorial Process Emerges from …

- Creative Scientists
- Research Programs
- Research Collaborations
- Peer Review
- Professional Activities
- Individual-Field-Domain Effects
  - $\mathrm{d}I/\mathrm{d}t = \gamma IN$

Conclusion

- Because combinatorial models work so well with respect to scientific creativity
- (and because they have been extended successfully to non-scientific creativity),
- they seem to provide a valid baseline for gauging other explanations.
- Hence the next question: What other processes or variables add an increment to the variance already explained by combinatorial models?