

G54SIM (Spring 2016)

Lecture 07 Input Modelling

Peer-Olaf Siebers

pos@cs.nott.ac.uk

Lecture Outline

- Part 1
 - Data and Information
 - Representing unpredictable variability
 - Random sampling
- Part 2
 - Case Study

Data and Information



Introductory Remark

- In this lecture we will focus on DES Input Modelling
 - Robinson (2004) Chapter 2 and 7
- More about SD Input Modelling
 - Luna-Reyes and Andersen (2003)
- More about ABS Input Modelling
 - Janssen and Ostrom (2006)
- Answers to the Top Ten Input Modeling Questions
 - Biller and Nelson (2002)

Data



- Data vs. Information

- Data

- Quantitative: numeric data

- e.g. cycle (service) times, breakdown frequencies, arrival patterns

- Qualitative: non-numeric facts or believes

- e.g. drawings of layouts, routing of automated guided vehicles, queuing behaviour

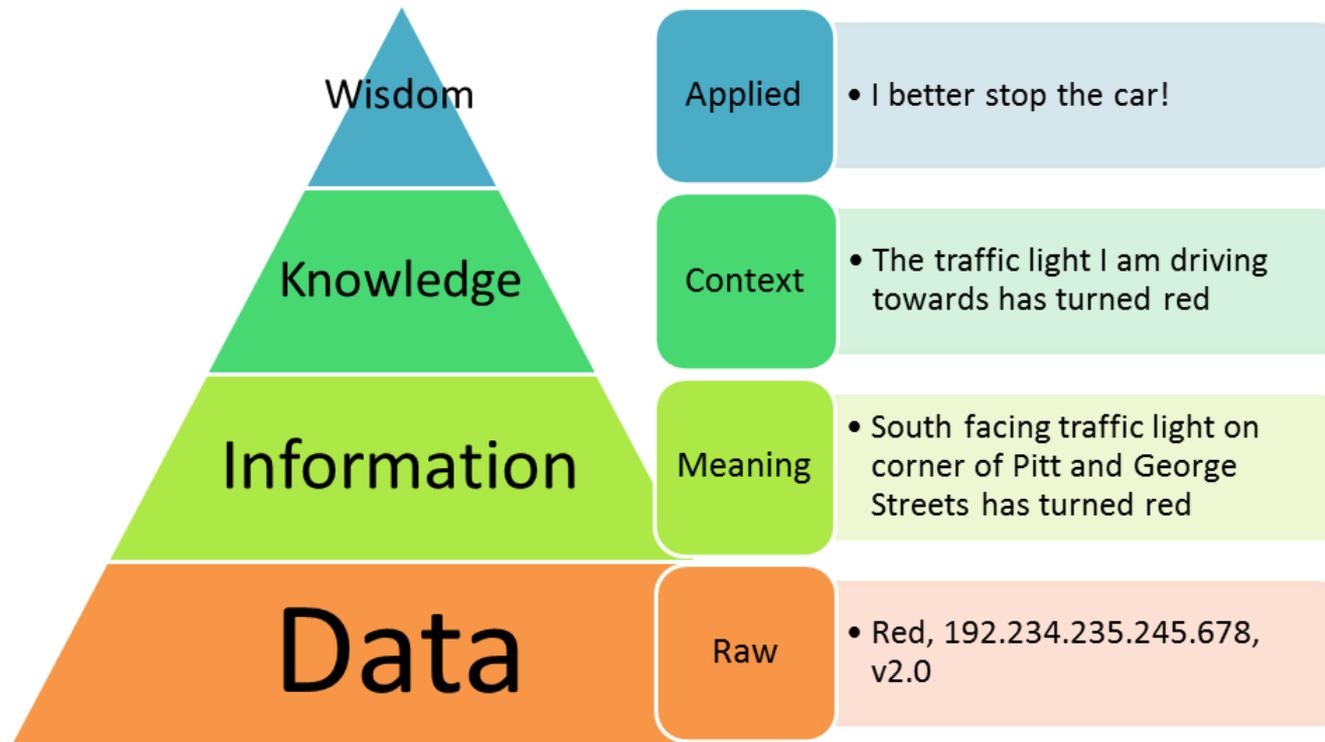
- Information

- Analysed data

- e.g. standard time (cycle time including allowances for breaks, skill level and process inefficiency), fitted statistical distributions

Data

- From Data to Wisdom [<http://www.allthingy.com/data-information-knowledge-wisdom/>]



Data

- Data requirements:
 - **Preliminary or contextual data:** Required for understanding the problem situation and for conceptual modelling
 - e.g. basic layout, believes about the cause of the problem
 - **Data for model realisation:** Directly identified from conceptual model
 - Deterministic data that have known and unchanging values
 - e.g. number of servers
 - Stochastic data that vary in an uncontrolled way (not completely!)
 - e.g. cycle times, machine break down patterns, customer arrival patterns, descriptions of customer types, scheduling and processing rules
 - **Data for model validation:** Used to ensure that every part of the model and the model as a whole is representing the real world system with sufficient accuracy

Data



- Case study from Lecture 3: Data Requirements
 - **Plot:** A fast-food restaurant is experiencing problems with one of its branches in its network. Customers regularly complain about the length of time they have to queue at the service counters.
 - **Objective:** Identify the number of service staff required during each period of the day to ensure that 95% of customers queue for less than 3 minutes for service.
 - **Constraint:** Due to space constraints, a maximum of six service staff can be employed at any one time.



Data

- Case study from Lecture 3: Data Requirements
 - Preliminary or contextual data:
 - Believes about the cause of the problem
 - Service standard requirements
 - Space restrictions
 - Data for model realisation:
 - Customer arrival rates (distribution)
 - Staff service times (distribution)
 - Staff rosters (table)
 - Data for model validation:
 - Proportion of customers queuing for less than 3 minutes
 - Waiting time for each customer
 - Staff utilisation

Data



- Obtaining data
 - Data needs to be *sufficiently accurate* and *in the right format* for the simulation model (more later)
 - Three categories of data:
 - Category A: *Available*
 - Data is known or has been collected before
 - Category B: *Not available* but *collectable*
 - Putting a data collection exercise in place by either getting people or electronic systems to monitor the operations
 - Category C: *Not available* and *not collectable*
 - Often occurs because the real world system does not yet exist or due to time limitation to collect meaningful data

Data

- Dealing with unobtainable Category C data
 - Estimate data
 - Use data from similar system for your estimates; using standard times; discuss with stakeholders; intelligent guess
 - Treat data as experimental factors
 - Instead of asking what the data are it is asked what do the data need to be (can only be applied when there is some control over the data in question)
 - Revise the conceptual model
 - Change the modelling objectives
 - Abandon the simulation study

Data

- Dealing with unobtainable Category C data (cont.)
 - Validity and credibility issues
 - Estimates need to be clearly identified in an assumption list
 - Sensitivity analysis should be performed on these data
 - Data might become available as project progresses

Data



- Data accuracy
 - Category A
 - Investigate the source of data; if data has been collected for a different purpose it might not be usable
 - Past is not always a good indicator of the future (e.g. pattern of breakdowns might change over time due to machine improvements)
 - If data is considered to be too inaccurate alternative sources should be sought; if this is not available it becomes Category B or C data
 - Category B
 - If collecting data make sure they are as accurate as possible (adequate sample size, minimise recording errors)
 - Make sure the data are not biased by peoples' personal interests (e.g. when staff is asked to collect data)

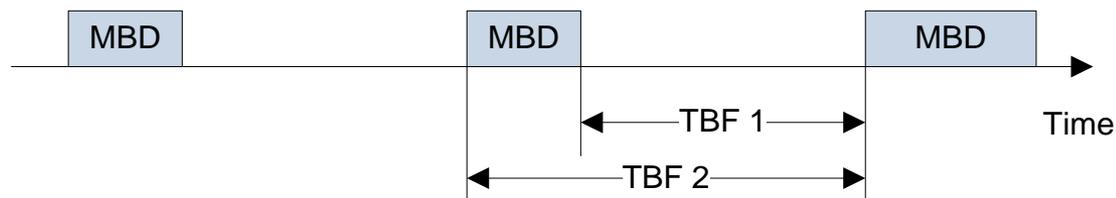
Data

- Data accuracy (cont.)
 - Category C
 - Estimates need to be clearly identified in an assumption list
 - Sensitivity analysis should be performed on these data
 - Data might become available as project progresses

Data

- Data format

- Information is often not in the right format for the simulation (e.g. time study data are aggregated to determine standard times for activities; in simulation the individual elements (e.g. breaks and process inefficiencies) are modelled separately)
- Important to know how the input data is interpreted by the simulation software



MBD = machine breakdown
TBF = time between failures



Small Group Activity

- You are hired by a furniture production company to optimise their sofa production line (this is a predominantly manual assembly line). For this task you are planning to use simulation.
 - What kind of data should you gather for your simulation model? Provide two examples for each data category and briefly state which category the data belongs to (and why) and how you could gather the data





Small Group Activity

- Some examples
 - Factory layout plan (category A): Updated whenever there are changes to the factory layout (e.g. position of production facilities); plans are usually available even if the factory does not exist yet
 - Productivity data (category A): Usually collected hourly and displayed somewhere in the factory to motivate staff (using electronic counters); if the factory exist historic data should be available
 - Cycle times (category B): time it takes to work on one sofa; collect data by using event loggers that record when a sofa arrives and when it leaves a work station; then you have to analyse the collected data



Small Group Activity

- Some examples
 - Machine breakdowns (category B): Can be measured when the maintenance crew has to get out to repair a machine; they could use a log that shows the start and end time of fixing the machine (one can then calculate the mean time between failures)
 - Future order arrivals (category C): Real system does not exist yet; one could use historic data (although this might not reflect the future; also there might not be any historic data available) or make this an experimental variable to test if the system can cope with various arrival rates
 - Poor data on machine failure (category C); Real system does not exist yet or does not exist for long enough to collect reliable breakdown data; try to collect data from a factory that uses the machine for a similar purpose or use the manufacturer guidelines

Representing Unpredictable Variability



Representing Unpredictable Variability

- Modeller must determine how to present the variability that is present in each part of the model
- Three options
 - Traces
 - Empirical distributions
 - Statistical distributions

Representing Unpredictable Variability

- Traces
 - Streams of data that describe a sequence of events
 - Data about the time the events occur (e.g. call arrival times)
 - Additional data about the event (e.g. call type)
 - Trace is read by the simulation as it runs and events are recreated in the model as described by the trace
 - Automatic monitoring systems are a common source of trace data



Call arrival time (minutes)	Call type
0.07	1
0.44	3
0.97	1
1.01	1
1.20	2
...	...



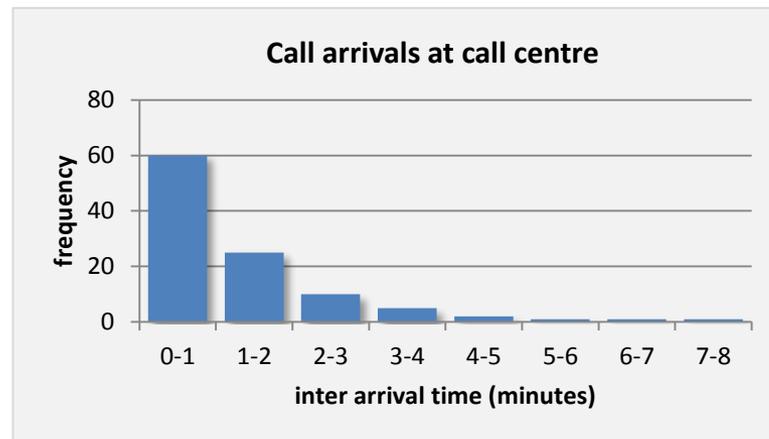
Representing Unpredictable Variability

- Traces
 - Advantages?
 - Most natural approach
 - Useful for validating a model against an existing system
 - Improve credibility of the model (client can see patterns they recognise)
 - Problems?
 - Real system needs to exist
 - Data set will be quickly exhausted in long simulations or those that are replicated many times
 - Tends to be slow as it involves intensive input operations (if the simulation model involves many sources of unpredictability)
 - Simulation model results are limited to those induced by this particular data set, and are thus not as generalisable as they should be

Representing Unpredictable Variability

- Empirical distributions
 - Show the frequency with which data values or ranges of values occur
 - Based on historical data, often formed by summarising trace data
 - As simulation runs values are sampled from the distribution
 - Most simulation software allows the user to enter empirical distribution data directly

arrival time	inter-arrival time
0	-
1.5	1.5
2	0.5
4.1	2.1
4.2	0.1
7.5	3.3
7.8	0.3
8.2	0.4



tableFunction

file

Properties Console Log

tableFunction - Table Function

General

Name: tableFunction Show name Ignore Public Show at runtime

Access: public Static

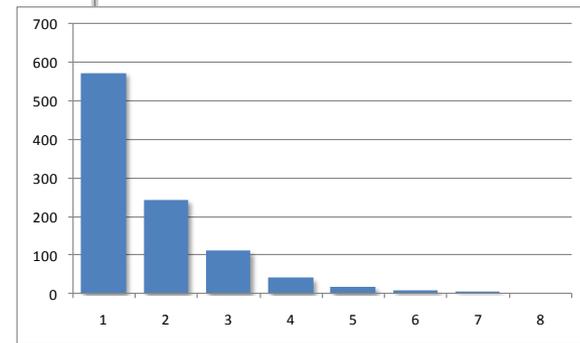
Interpolation: Step

Out of Range: Error

Table Data:

Argument	Value
0	60
1	25
2	10
3	5
4	2
5	1
6	1
7	1

	A	B
1	1.317251	
2	0.254577	
3	4.004593	
4	4.913536	
5	3.897737	
6	0.266942	



Properties Console Log

Main - Active Object Class

General

Name: Main Ignore

Agent Generic

Startup code:

```

Random r=new Random(1);
CustomDistribution n=new CustomDistribution(tableFunction, r);
for(int i=0;i<1000;i++){
    file.print(n.get()+",");
}

```

Properties Console Log

Main - Active Object Class

Advanced

Imports section:

```
import java.util.Random;
```



Representing Unpredictable Variability

- Empirical distributions
 - Advantage?
 - There is almost no issue of poor fit, as there is little or no fitting going on
 - Generating draws from such empirical distributions is easy and fast, using linear interpolation
 - It is possible to change the stream of random numbers used for sampling and alter the pattern of variability (important when performing multiple replications)
 - Problems?
 - Range of variability is still restricted to that observed in historic events
 - With a small sample size this method tends to be high-variance, not filling in the 'holes' well at all

Representing Unpredictable Variability

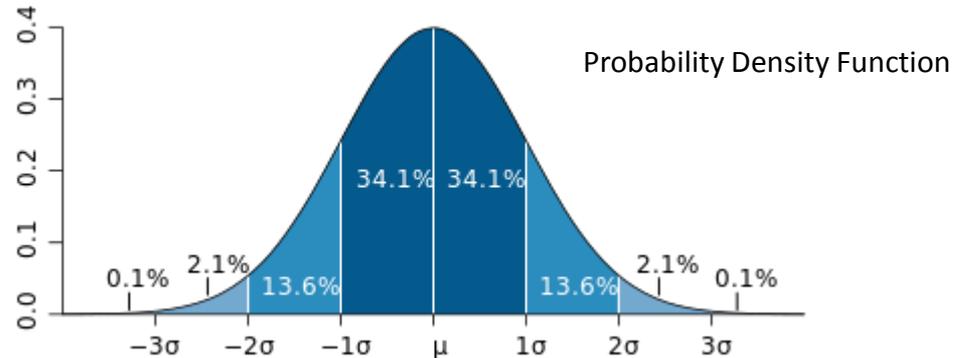
- Statistical distributions
 - Defined by some mathematical function or probability density function
 - Three different types of statistical distributions
 - ***Continuous distributions***: For sampling data that can take any value across a range
 - ***Discrete distributions***: For sampling data that can take only specific data across a range, for instance only integer or non-numeric values
 - ***Approximate distributions***: Used in the absence of data
 - Process for sampling distributions is explained later

Representing Unpredictable Variability

- Statistic distributions commonly used in simulation models
 - *Continuous* distributions
 - Normal distribution
 - (Negative) exponential distribution
 - Erlang distribution
 - *Discrete* distributions
 - Binomial distribution
 - Poisson distribution
 - *Approximate* distributions
 - Discrete and continuous uniform distribution
 - Triangular distribution
 - For more details see Law and Kelton (2006) or Wikipedia

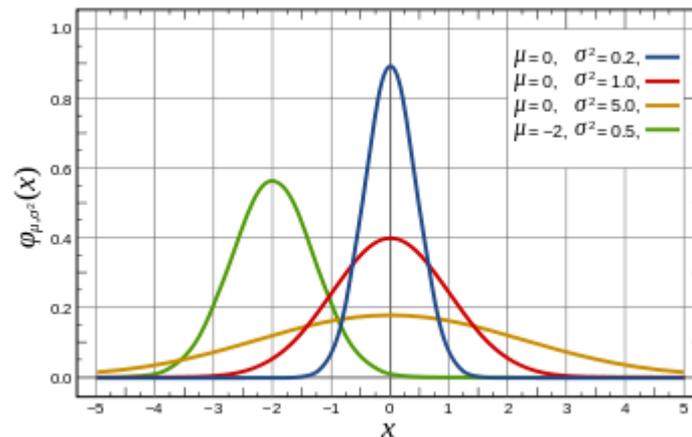
Representing Unpredictable Variability

- Continuous: Normal distribution (Gaussian distribution)
 - x axis: Values of the dependent variable (e.g. height)
 - y axis: Probability that the values of the dependent variable will occur
 - 68% of values less than one standard deviation away from the mean
 - 95% of values less than two standard deviations away from the mean
 - 99.7% of values less than three standard deviations away from the mean



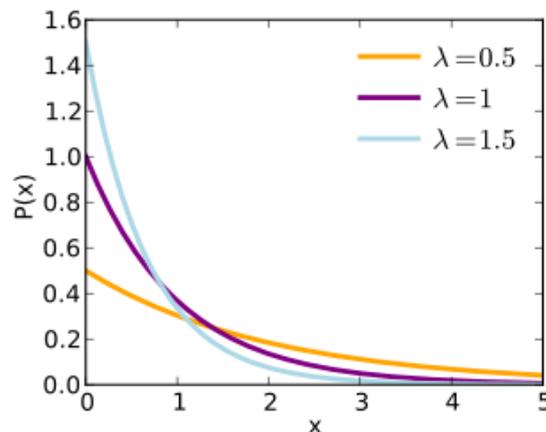
Representing Unpredictable Variability

- Continuous: Normal distribution (Gaussian distribution)
 - Parameters: Mean (its location) and standard deviation (its spread)
 - For a given range of values of x , the area under the curve gives the probability of obtaining that range of values
 - Used for sampling errors; sometimes truncated normal distribution is used (e.g. when sampling for times) to avoid negative values



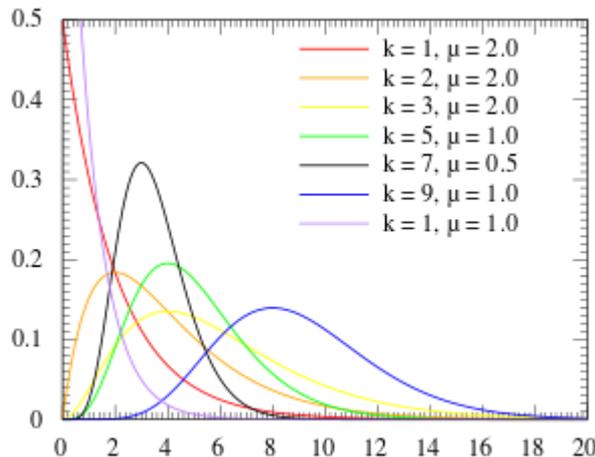
Representing Unpredictable Variability

- Continuous: (Negative) exponential distribution
 - Parameter: Mean ($1/\lambda$ = inter arrival time, λ =rate parameter)
 - Gives a high probability of sampling values close to zero and a low probability of sampling higher values
 - Used for sampling times between events or times to complete a task (problem: high probability of near zero values)



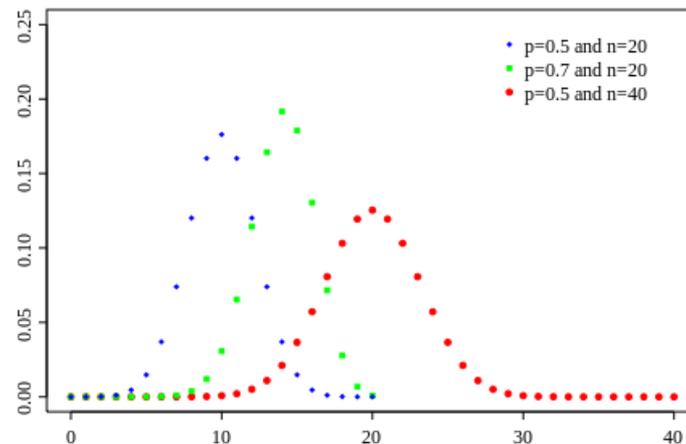
Representing Unpredictable Variability

- Continuous: Erlang distribution
 - Parameters: Mean and k (determines the skew of the distribution)
 - If k equals 1 the Erlang distribution is the same as a negative exponential distribution with an equivalent mean
 - As the value of k increases, the skew reduces and the hump of the distribution moves towards the centre
 - Used for sampling the time to complete a task and inter arrival times



Representing Unpredictable Variability

- Discrete: Binomial distribution
 - Parameters: Probability of success (p) and number of trials (n)
 - Describes the number of successes in a sequence of n independent yes/no experiments, each of which yields success with probability p

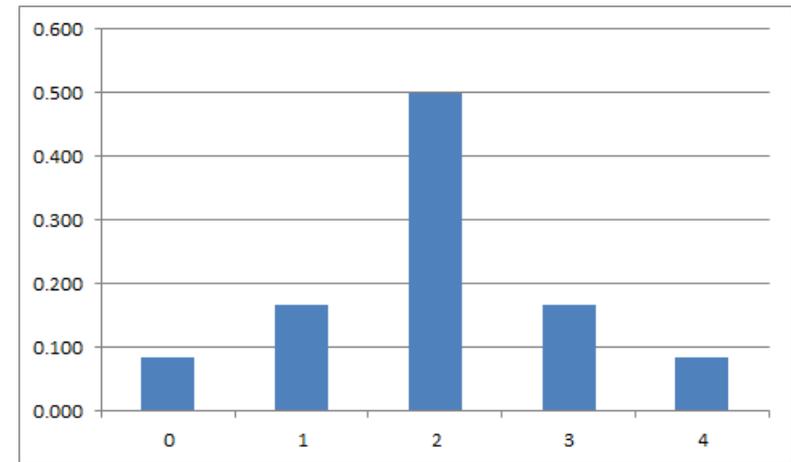


Representing Unpredictable Variability

- Discrete: Binomial distribution example (4 coin flips)

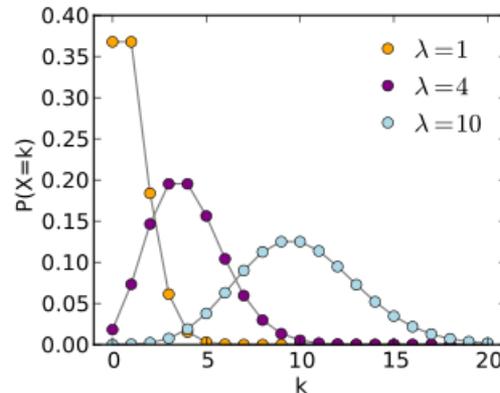
Outcome	Flip 1	Flip 2	Flip 3	Flip 4	Number of Heads
1	h	h	h	h	4
2	t	h	h	h	3
3	t	t	h	h	2
4	t	t	t	h	1
5	t	t	t	t	0
6	h	t	h	h	2
7	h	h	t	h	2
8	h	h	h	t	3
9	h	t	t	h	2
10	h	h	t	t	2
11	h	t	t	t	1
12	t	h	h	t	2

	Number of Heads	Occurance	Probability
	0	1	0.083
	1	2	0.167
	2	6	0.500
	3	2	0.167
	4	1	0.083
Sum	/	12	1



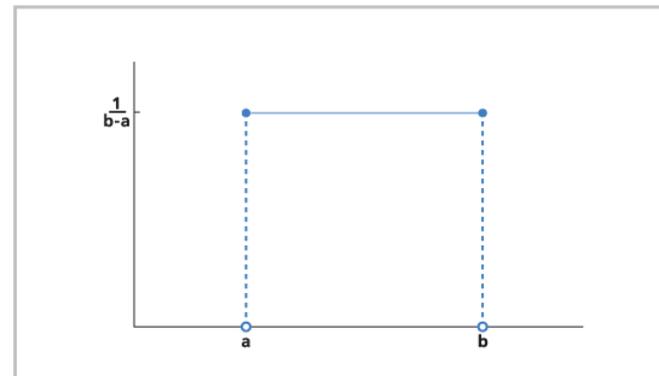
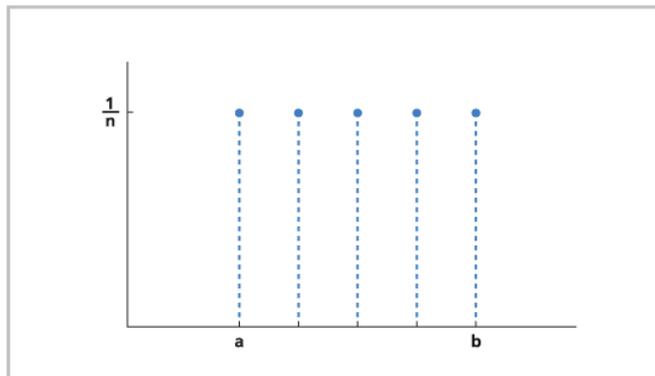
Representing Unpredictable Variability

- Discrete: Poisson distribution
 - Parameter: Mean (λ = rate parameter; positive number representing the expected number of occurrences within a specified interval, e.g. if the event occurs every 10 minutes, in an hour λ would be 6)
 - Represents number of events that occur in an interval of time
 - Used for sampling arrival rates, number of items in a batch of random size (e.g. Number of boxes on a pallet)



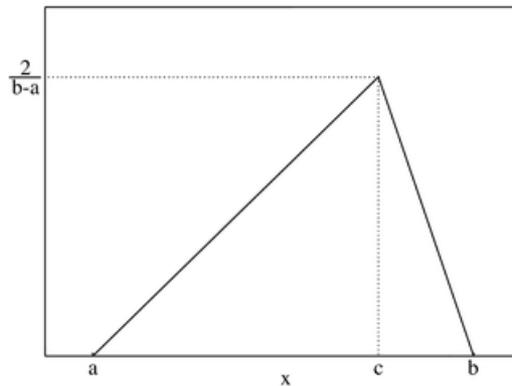
Representing Unpredictable Variability

- Approximate: Uniform distribution
 - Parameter: Minimum and maximum
 - Provide a useful approximation in the absence of data
 - Frequently used when dealing with category C data
 - Discrete and continuous uniform distribution



Representing Unpredictable Variability

- Approximate: Triangular distribution
 - Parameters: Minimum, maximum, mode (value that occurs the most frequently in a data set)
 - Mean and mode can be quite different; this needs to be considered when collecting data
 - Used as an approximation for task times and inter arrival times



Representing Unpredictable Variability



- Statistical distributions
 - Advantages?
 - Range of variability is not restricted to that encountered in the past
 - Limited use of computer memory
 - Not necessary to have data from the real system as parameters can be estimated; however, data from the real system is always preferred
 - Problems?
 - Many statistical distributions have long tails and therefore there might be occasions when extreme values might be sampled
 - Least transparent approach for the client
 - Possibility of direct comparison to historic results not available
 - Wanting to find a fit to our observed data from among a relatively short list of probability distributions that were developed decades ago largely for their analytic tractability.

Representing Unpredictable Variability

- Fitting empirical data to statistical distributions
 - Three step process
 1. Select a statistical distribution
 2. Determine the parameters
 3. Test of goodness of fit
 - Iterative process
 - It is not enough to select a single distribution or a single set of parameters; a series of distributions should be tried with different sets of parameter values

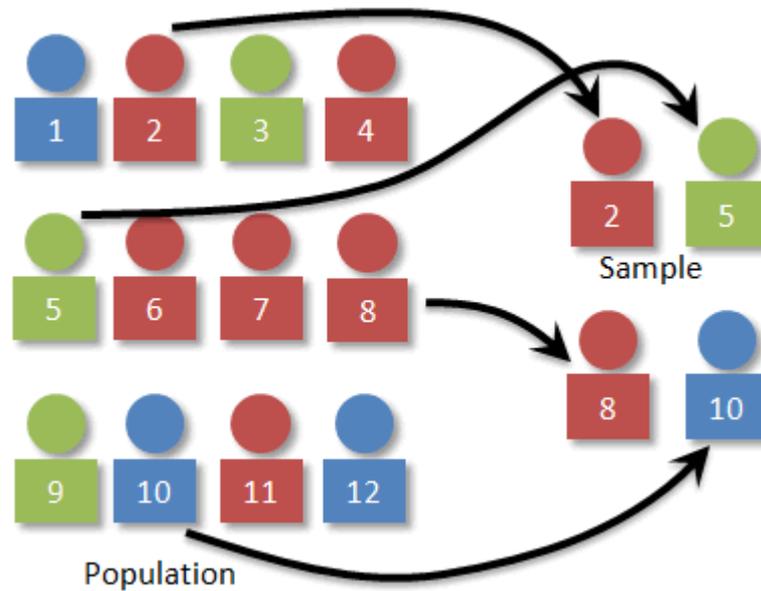
Representing Unpredictable Variability

- Fitting empirical data to statistical distributions
 - Select a statistical distribution
 - Inspect the data
 - Select distribution based on known properties of the process
 - Determine parameters
 - Means can be calculated from histogram data
 - Some parameters cannot be estimated: use trial and error
 - The goodness-of-fit test
 - Graphical test
 - Comparing the histogram of the empirical data with that of the proposed distribution
 - Statistical test (see Robinson, 2004, pp114-119)
 - Software: e.g. ExpertFit and StatFit

Representing Unpredictable Variability

- Case study from Lecture 3: Data Representation + Category
 - Preliminary or contextual data:
 - Believes about the cause of the problem [A]
 - Service standard requirements [A]
 - Space restrictions [A]
 - Data for model realisation:
 - Customer arrival rates {exponential distribution} [A or B]
 - Staff service times {Erlang distribution} [A or B]
 - Staff rosters {table} [A]
 - Data for model validation:
 - Proportion of customers queuing less than 3 minutes {%}
 - Waiting time for each customer {histogram}
 - Staff utilisation {%}

Random Sampling



Random Sampling

- Sampling
 - Example: Booking clerk with one arrival process
 - 60% of customers: Personal enquirers (= type X)
 - 40% of customers: Phone callers (= type Y)
 - Top hat method:
 - 100 pieces of paper, 60 with X and 40 with Y
 - Every time a customer arrives draw one piece
 - Important to replace the paper to keep the ratio (60:40)
 - In computer simulation a similar principle is adopted based on random numbers

Random Sampling

- Random numbers:
 - Sequence of numbers that appear in a random order
 - Presented as integer (e.g. [0-99]) or as real numbers (e.g. [0-1[))
 - Top head method (replacement method)
 - Properties
 - **Uniform:** same probability of any number occurring at any point in the sequence
 - **Independent:** once a number has been chosen this does not effect the probability of it being chosen again or of another number being chosen

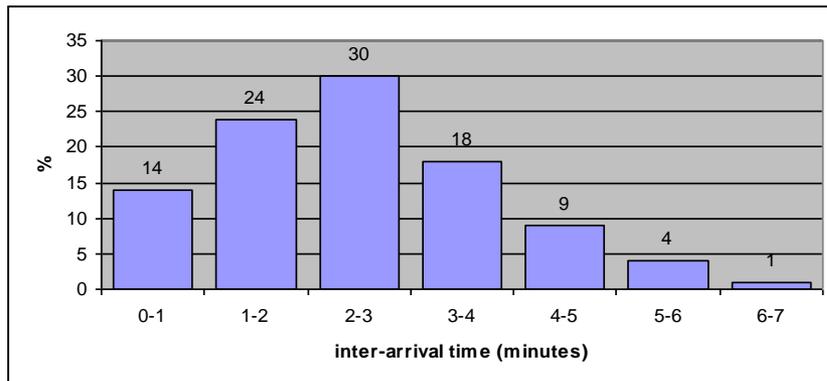
Random Sampling

- Relating random numbers to variability in a simulation
 - Modelling proportions
 - Example: Booking clerk with one arrival process
 - For small sample sizes ratio might not be achieved (as the process is random)
 - For large sample sizes ratio will be achieved more or less

Random numbers	Customer type
00-59	X
60-99	Y

- Modelling variability in times

- To model continuous real variables (e.g. activity times) one could determine the range and then draw a second random number, divide it by 100 and add it to the range

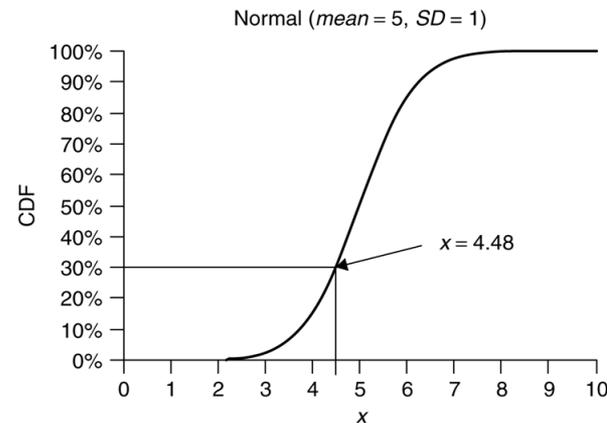
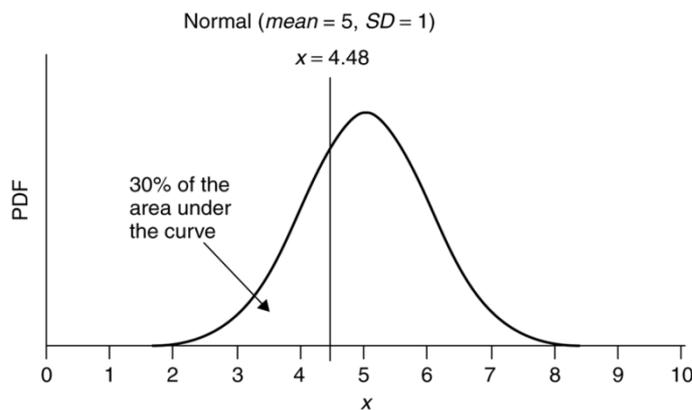


Random numbers	inter arrival time
00-13	0-1
14-37	1-2
38-67	2-3
68-85	3-4
86-94	4-5
95-98	5-6
99	6-7

Customer	rnd 1	range	rnd 2	inter arrival time
1	41	2-3	27	2.27
2	44	2-3	24	2.24
3	90	4-5	5	4.05

Random Sampling

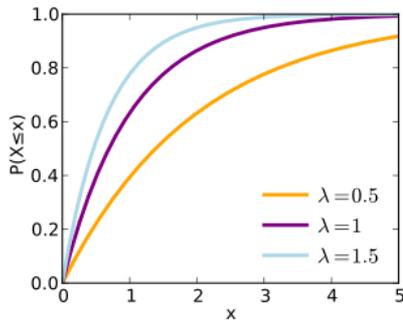
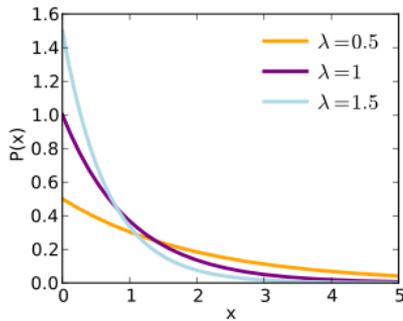
- Random sampling (generating variates) from standard statistical distributions
 - To sample a value from the distribution the random number is taken to be the percentage of the area under the curve
 - Difficult to think in terms of identifying area under the curve
 - Instead of the probability density function (pdf) we use the cumulative distribution function (cdf)



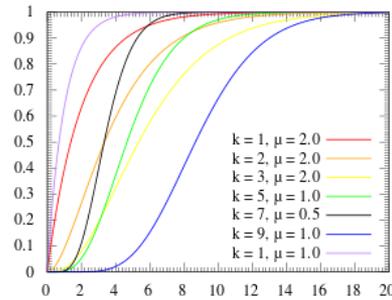
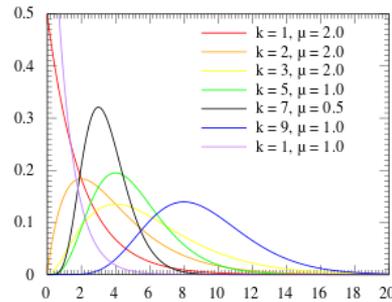
Random Sampling

- More PDF / CDF pairs

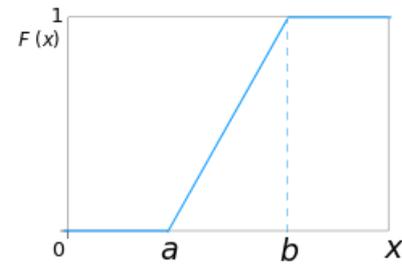
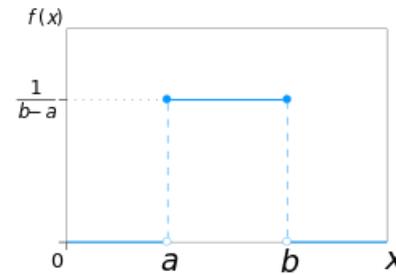
(Negative) Exponential



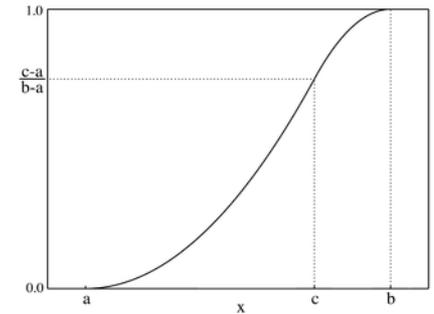
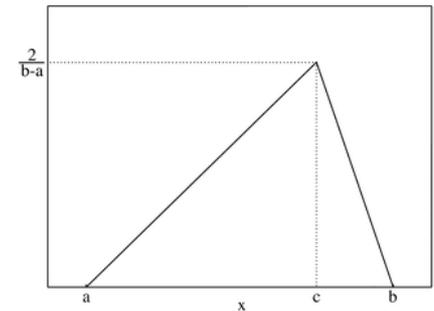
Erlang



Uniform



Triangular



Random Sampling

- Computer generated random numbers
 - By nature computers do not behave in a random fashion
 - There are algorithms that give the appearance of producing random numbers although the results are completely predictable
 - Numbers produced by these algorithms (called pseudo random numbers) have the properties of uniformity and independence
 - Commonly used algorithm for generating random numbers:
 - $X_{i+1} = aX_i + c \pmod{m}$
 - X_i : Stream of random numbers (integer) on the interval (0, m-1)
 - a: Multiplier constant
 - c: Additive constant
 - m: modulus
 - X_0 = starting value for X = seed

Random Sampling

- Computer generated random numbers (cont.)
 - Issues to think about when using random number generators
 - **All generators will eventually cycle**, i.e. they return to their starting point and generate the same sequence of random numbers again.
 - **Cycles should be easily divided into streams** which are non-overlapping random-number sub-sequences that are themselves astronomically long, and which can be addressed easily by the modeller.
 - For more details on these issues see Kelton (2009)
 - For more details on Random Number Generators see L'Ecuyer (2006)

Case Study

Using Simulation to Assist Recruitment in Seasonally Dependant Contact Centers

Leeanne May

Peer-Olaf Siebers

For more information see: May and Siebers (2015)

Introduction

- The weather is unpredictable and can have a large impact on the profitability of seasonal businesses, particularly if staffing requirements are highly temperature-dependent
- An example for such a business is a company that provides boiler maintenance and repair services
 - In particular their Call Centre (CC) staffing level requirements depend very much on the severity of the winter
 - The likelihood of boilers breaking down during winter is correlated to the severity of the winter



Introduction

- Challenge
 - If recruitment starts too early then staff will have increased idle time
 - If recruitment starts too late and the work increases faster than staff can cope, there will be lots of complaints and lost customers
- Aim
 - To develop a novel simulation tool that helps managers to make better informed decisions about their CC recruitment needs (of permanent an temporary staff)
 - Timing for hiring new staff
 - Deciding about the optimal length of temporary contracts

Tool Development



- Conceptualisation

- Problem

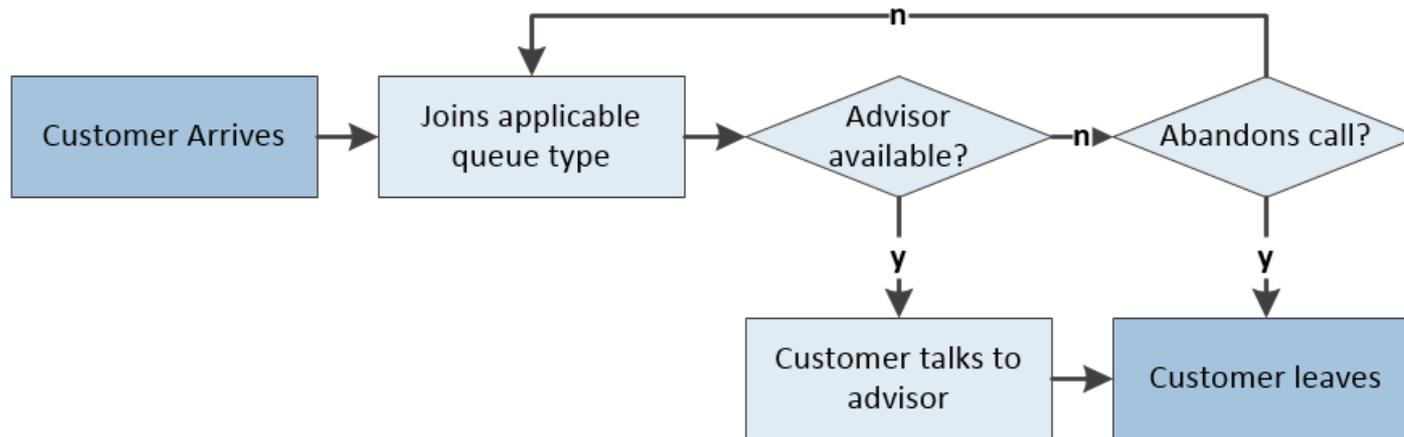
- A boiler maintenance and repair company receive calls from customers throughout the year to book appointments. Service calls stay reasonably constant throughout the year, however breakdown calls increase during colder months. Staffing levels need to be increased in order to meet service level targets, however level is determined by financial constraints.

- Objectives

- Consistently meet these KPIs from June to May
 - Average time in system of customers < 6 min.
 - Abandonment rate < 5%
 - Calls answered within 20 sec. > 90%
 - Calls per advisor per hour: 6-8

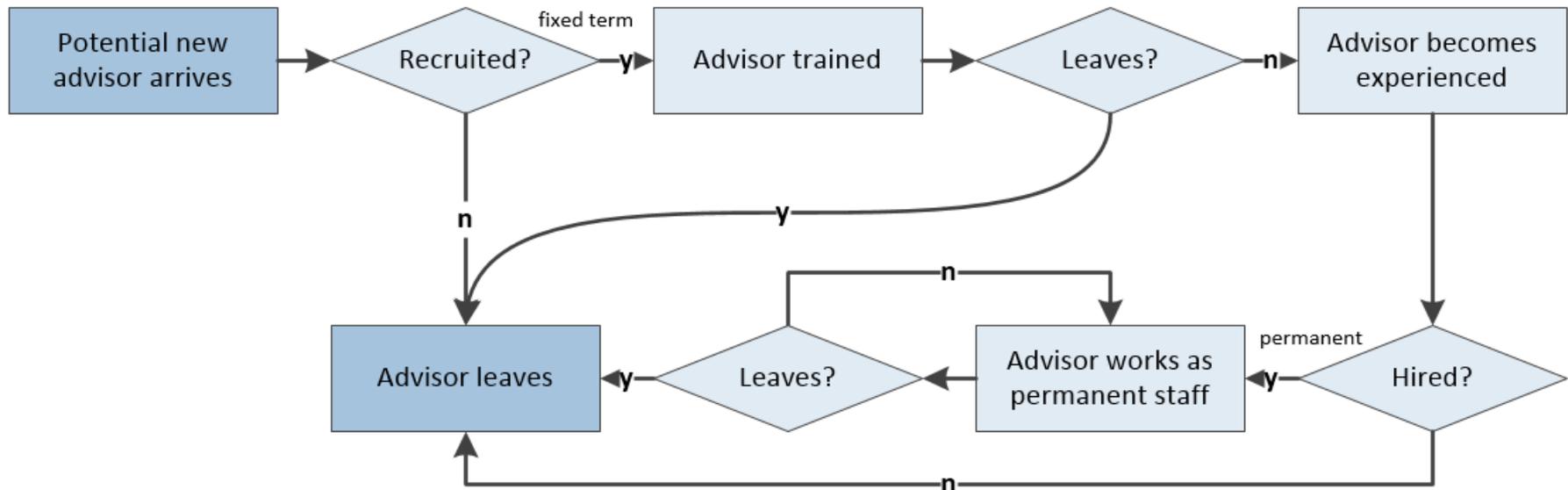
Tool Development

- Conceptual Model
 - Call Centre (CC): Call process



Tool Development

- Conceptual Model
 - Call Centre (CC): Recruitment Process



Tool Development

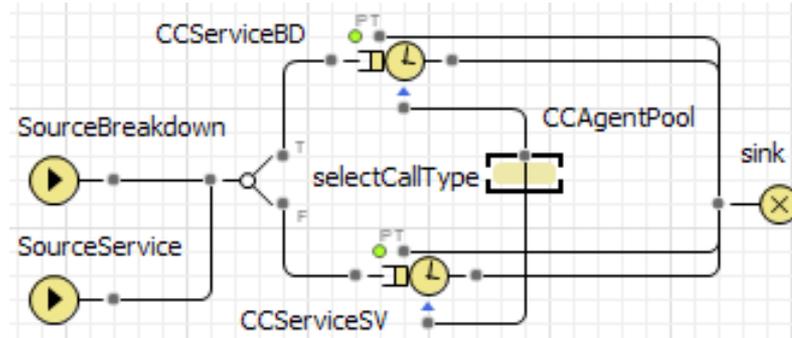
- Conceptual Model
 - Call Centre Advisor (CCA) and Calls (C)
 - Passive agents: Individual objects with a list of attributes to give them a personal identity but do not initiate any actions and do not have any specific goals

Call Centre Advisor Class
<ul style="list-style-type: none">• Type (permanant or fixed term)• Level of training• Time till leave

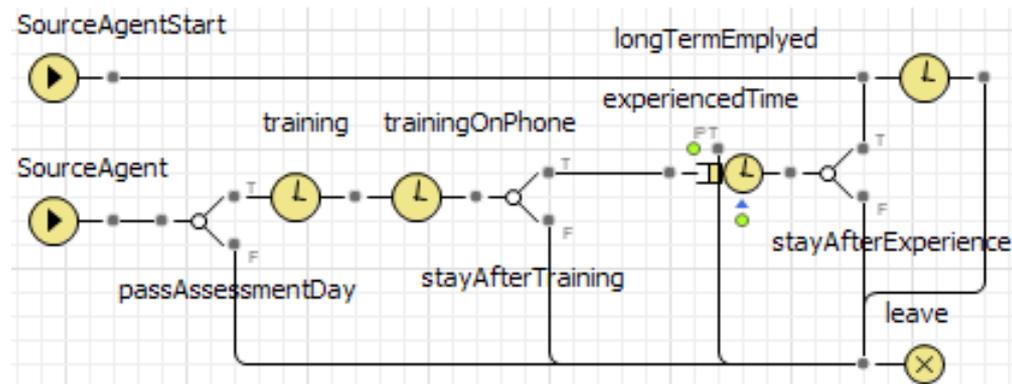
Call Class
<ul style="list-style-type: none">• Type (Service or breakdown)• Time till abandon• Time enter queue• Time leave queue• Time enter system• Time leave system

Implementation

- Call Processes



- Recruitment process



Implementation

- Agents

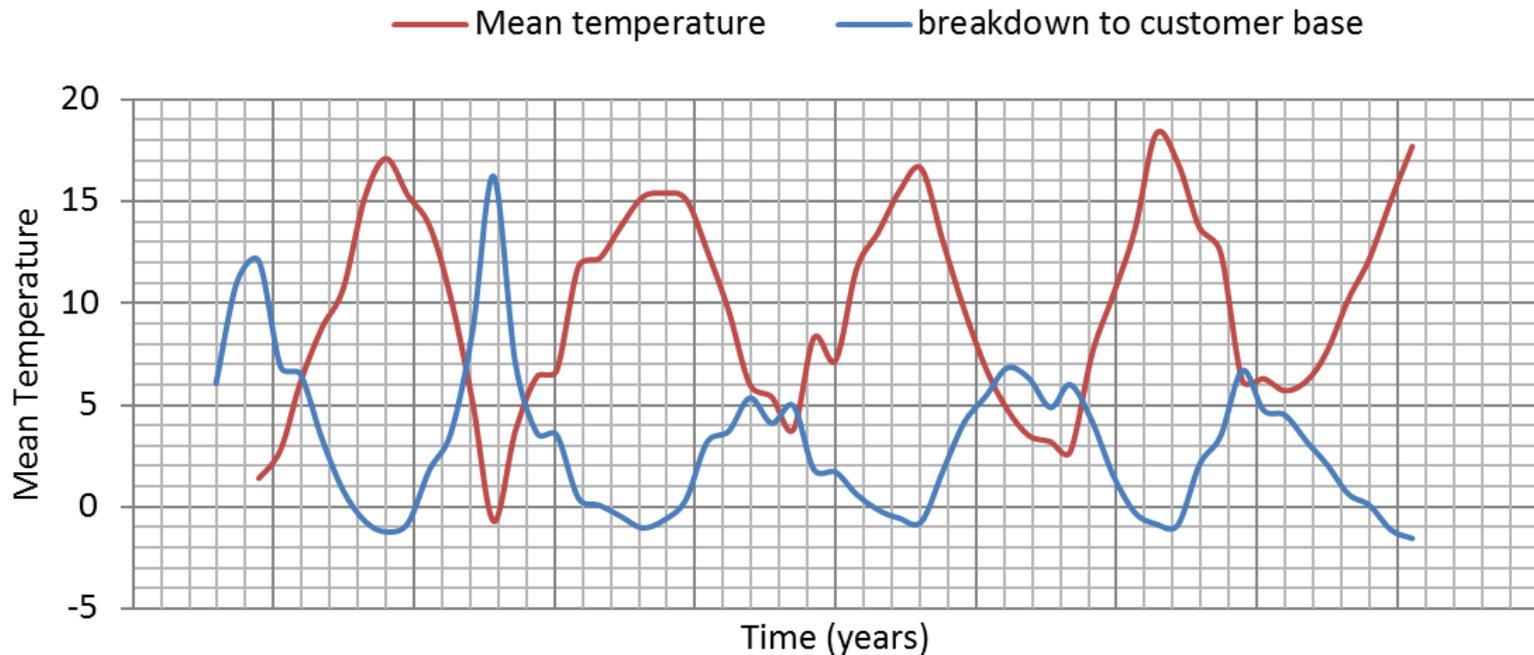
Call Type	Time Till Abandon
Service	$\text{entity.dblTimeTillAbandon} = \text{lognormal}(4.11051, 1.36609, 0)/60;$
Breakdown	$\text{entity.dblTimeTillAbandon} = \text{lognormal}(4.56343, 1.44683, 0)/60;$

Call Type	Service Time Distribution
Service	$(\text{lognormal}(5.47917, 0.506602, 0)/60) * \text{vServiceTimeModifier}$
Breakdown	$(\text{lognormal}(5.79643, 0.614067, 0)/60) * \text{vServiceTimeModifier}$
$\text{vServiceTimeModifier} = ((\text{vStaffTraining} * 1.4) + (\text{vStaffTrained} * 1.2) + (\text{vStaffPermanent} * 1)) / \text{pNoCCAgentsAvailable}$	

CCAgent Object	Time till Leave			Effectiveness
	min	max	mode	
Permanent	4 weeks	3 year	1 years	1
Fixed-Term Training	2 weeks	7 months	6 months	0.6
Fixed-Term Experienced	2 weeks	7 months	6 months	0.8

Implementation

- Relationship between weather and incoming breakdown calls



BD calls as proportion of Customer Base [values redacted]

Implementation

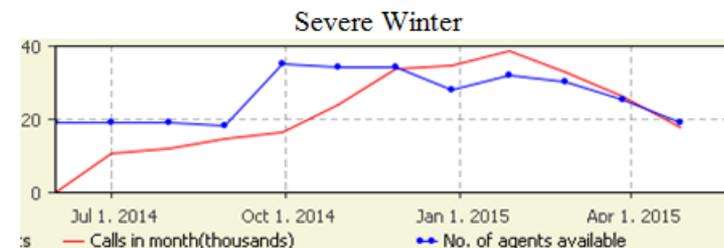
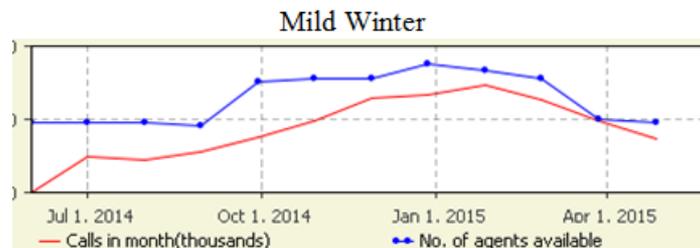
- With a bit of clever stats we were able to represent the relationship between calls and different severity of winters

$$y=0.0406304264574+0.00035647283404701*x \quad (1)$$

$$\text{degreeDayVal}=(\text{degreeDayDistr_peak}-\text{degreeDayDistr_min}) * \exp(-\text{pow}(\text{month}-\text{degreeDayDistr_month}, 2) / (2 * \text{pow}(\text{degreeDayDistr_width}, 2))) + \text{degreeDayDistr_min} \quad (2)$$

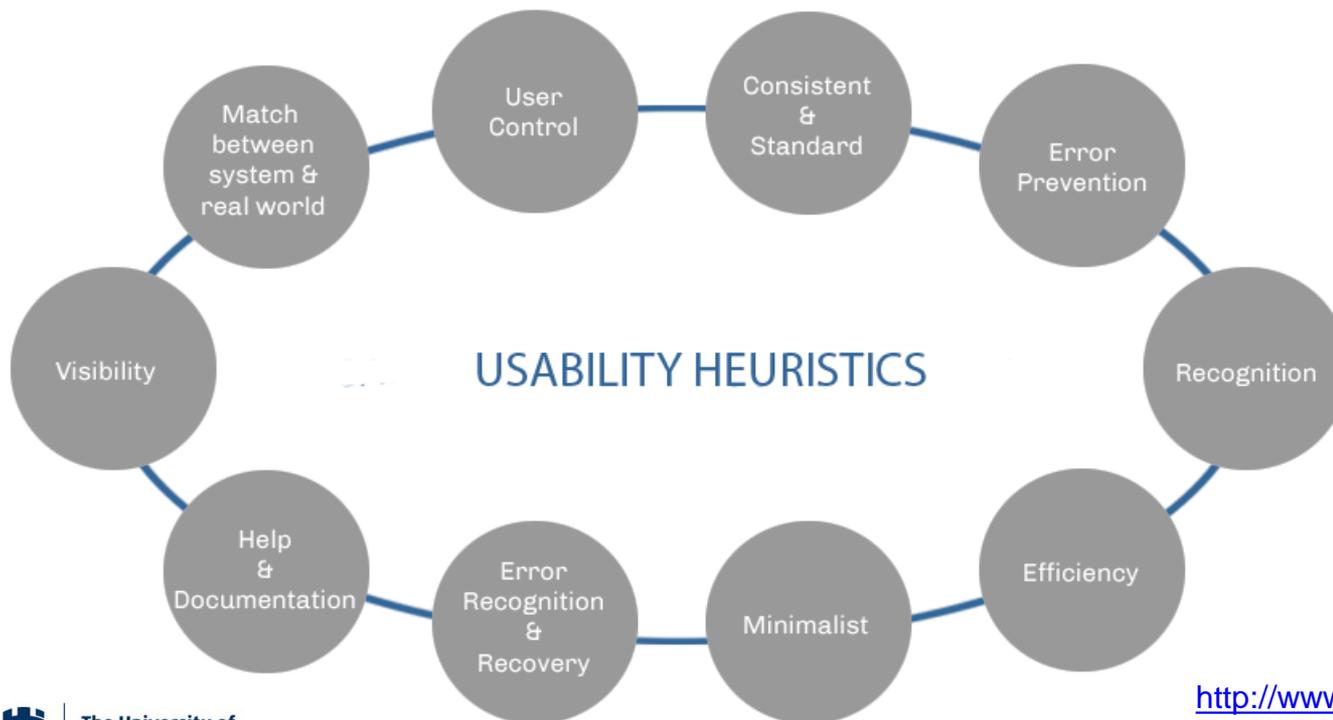
$$\text{bdFrac}=0.0406304264574+(0.00035647283404701 * \text{degreeDayVal}) \quad (3)$$

$$\text{feedbackMonth}=(\text{initCustBase} * \text{bdFrac}) + (\text{initCustBase} * 0.08) \quad (4)$$



Graphical User Interface

- Tool is supposed to be used by managers
 - We used Nielsen's heuristic usability principles (Nielsen 1993)
 - Usability tests confirmed usefulness of tool for management



<http://www.designui.net/process.html>

Contact Centre Long Term Recruitment Tool

This is a tool allows you to see the potential outcome of your chosen FTE over the winter period. Choose the starting FTE and the target FTE . Try different levels of severity of winter and change the customer base to change the number of calls. The simulation starts in June and will automatically pause at the start of the following May.

Enter August FTE staff:

Enter mid-October target FTE staff:

Enter customer base:

Press Enter to update the feedback

Select weather profile:

- Mild winter
- Average winter
- Severe winter

The settings chosen will provide around this many calls in October:

V feedbackMonth
14,306

The settings chosen will provide around this many calls a day in October:

V feedbackDay
476

Run the model



Choose Speed

Real Time

50x 500x

Maximum

Choose View

Year Output

Month Output

Day Output

Model Working

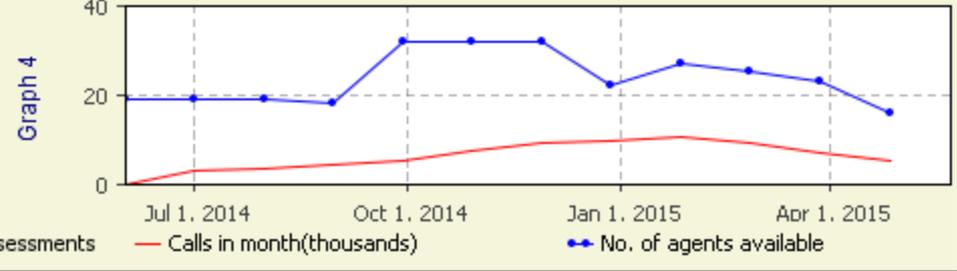
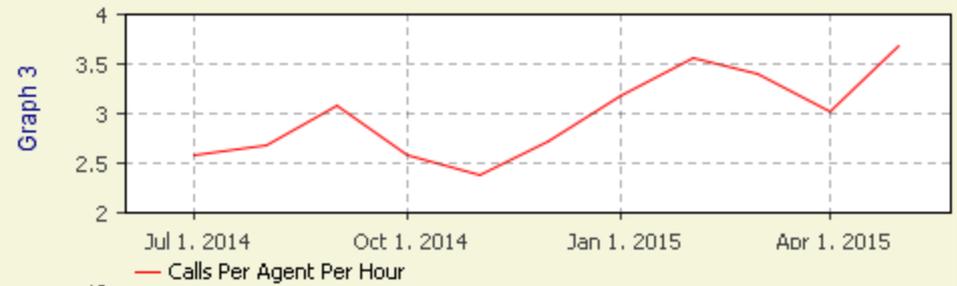
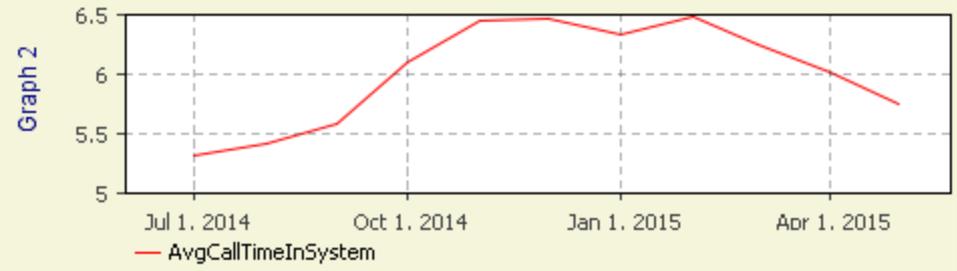
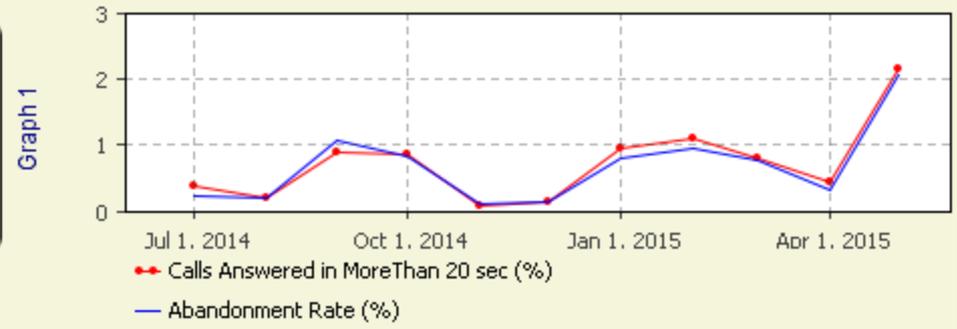
Graph 1 is an indicator of how well the call centre advisors have dealt with the call queue. The target is < 5% abandonment and <10% calls answered in more than 20 seconds. If these targets are being easily met it is a sign that advisors have more availability.

Graph 2 is an indicator as to the length of time the call takes to be completed. If the graph 1 targets are being met then times longer than 5 minutes suggests that there is a high ratio of untrained to experienced staff.

Graph 4 shows calls per agent per hour. This is an indicator as to how well the agents are being utilised.

Graph 5 shows the weather and recruitment process. The higher the degree days the colder it was and the vNoOfAssessments shows how many assessment centres (or weeks) it took to hire the target amount of advisors.

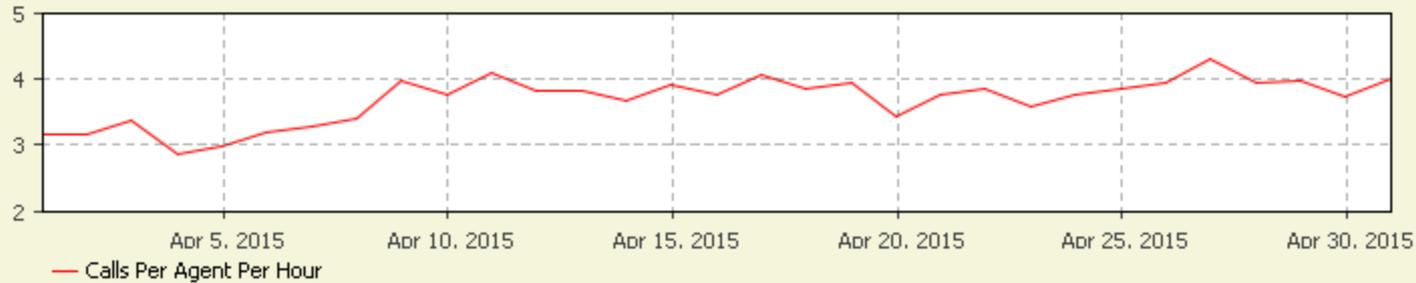
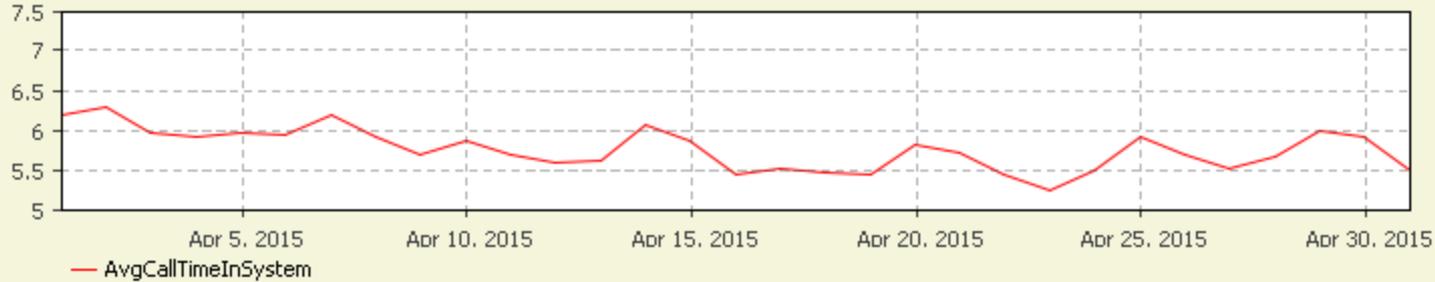
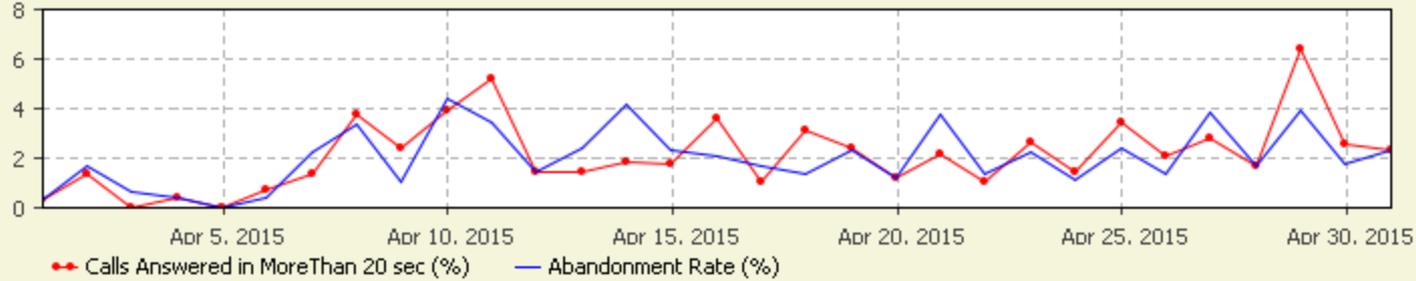
The call centre runs for 24 hours but monthly graphs only include data collected between 8am and 8pm.



Choose Speed		Choose View	
Real Time		<input type="radio"/> Year Output <input checked="" type="radio"/> Month Output <input type="radio"/> Day Output <input type="radio"/> Model Working	
50x	500x		
Maximum			



For information about how to use the graphs is available from the Mont Output view.



Choose Speed

Real Time

50x 500x

Maximum

Choose View

Year Output

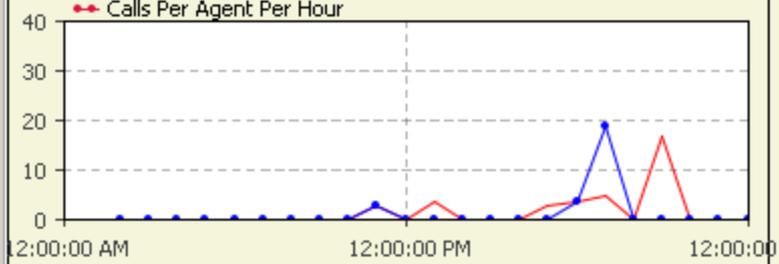
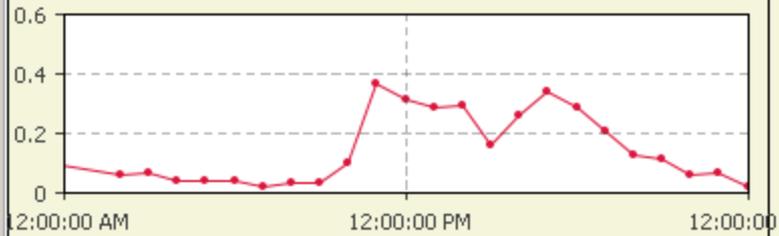
Month Output

Day Output

Model Working



Stop and Return to Main Screen



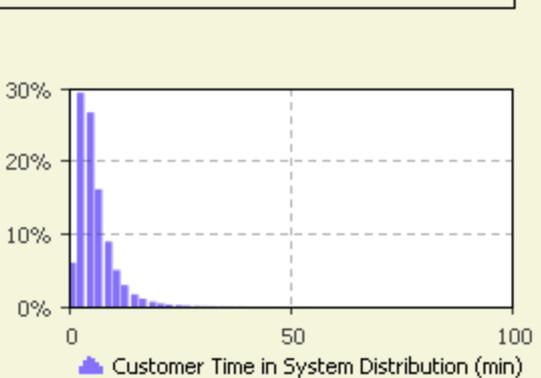
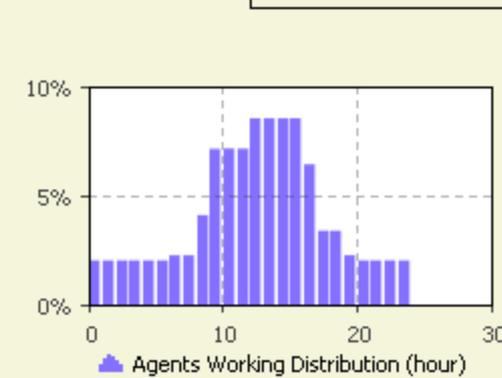
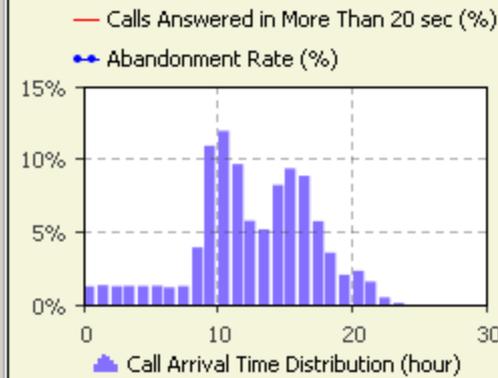
Training (had 1 week basic training)

Original Agent New Agent

- vStaffTraining 0
- vStaffTrained 0
- vStaffPermanent 16
- vServiceTimeModifier 1
- pNoCCAgentsAvailable 16
- pNoCCAgentsInPool 3

Trained and Experienced

Detailed description: A visual representation of the agent pool. It shows a group of blue icons (Original Agents) and a few cyan icons (New Agents). The icons are arranged in a cluster, representing the distribution of agents in the system.



Future Plans

- Agent design
 - Creating active agents by extending the existing passive agents
 - Designing archetypes
 - Considering bounded rationality
 - Consider agent memory (e.g. about service quality)
- Impact of using intelligent agents
 - Test the impact of such agents on output accuracy

Questions / Comments



Acknowledgement

- Slides are based on Robinson (2004) Chapter 2 and 7
- The distribution figures are taken from Wikipedia

References

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