User Clustering and Traffic Prediction in a Trunked Radio System

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ROADMAP

- Introduction
- E-Comm network
- Traffic data
- User clustering
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- Conclusions
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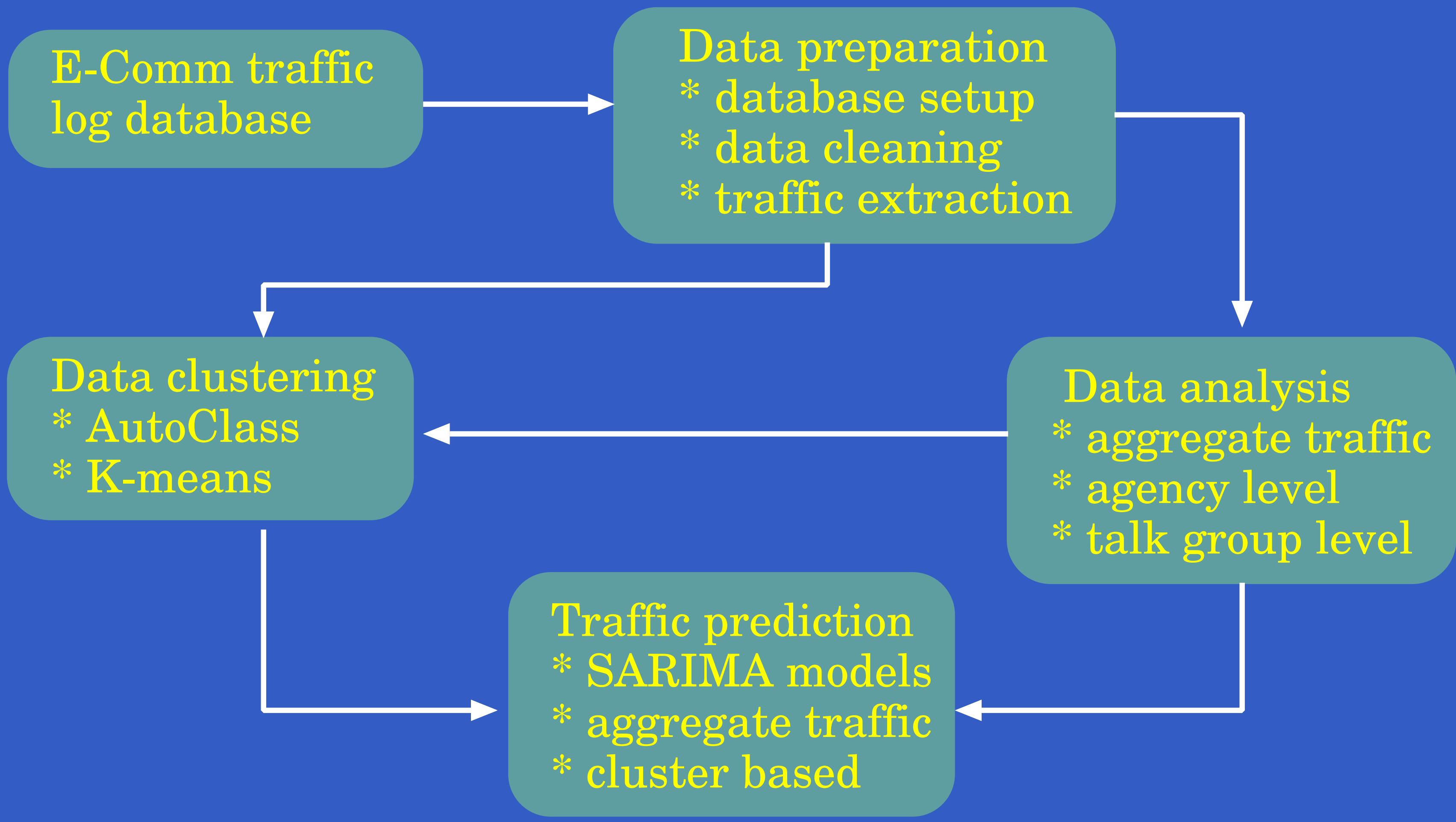
MOTIVATION

- Analysis of traffic from operational wireless networks enables:
  - better understanding of user behavior patterns
  - better quality of service.
- Traffic prediction methods:
  - “Top-down” approach: based on aggregate traffic.
  - “Bottom-up” approach: focuses on individual users.
  - Our approach: user cluster based prediction.

PRIOR DATA ANALYSIS

- User behavior and mobility patterns exhibit daily and weekly patterns [Tang and Baker, 1999].
- User behavior in Cellular Digital Packet Data (CDPD) mobile wireless networks has similar cyclic patterns [Andriantiatsaholiniaina and Trajković, 2002].
- Trunked radio network traffic [Sharp et al., 2004]:
  - call holding time distribution is approximately lognormal
  - call inter-arrival time is closely approximated by an exponential distribution.

OUR RESEARCH



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E-COMM NETWORK

- Regional emergency communications center.
- Covers Greater Vancouver Regional District (GVRD) – 11 systems/cells.
- Provides emergency dispatch/communication services.
- Serves 16 agencies such as RCMP, fire and rescue, police, and ambulance.
- Employs Enhanced Digital Access Communications System (EDACS).

E-COMM NETWORK COVERAGE

GROUP/MULTI-SYSTEM CALLS

- A group call is a standard call made in a trunked radio system.
- EDACS network operators have observed that more than 85% of calls are group calls.
- A multi-system call is a single group call involving more than one system/cell.
- More than 55% of group calls are multi-system calls.

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TRAFFIC DATA

- Raw event log generated from a distributed database system.
- Events generated in the network from March 1^{st} 00:00:00 2003 to May 31^{st} 23:59:59 2003.
- The size of the original data is $\sim$ 6 GBytes, with 44,786,489 record rows for the 92 days of data.
- From the 26 original fields in the database, 9 fields are of interest for our analysis.

DATA SAMPLE

no.	event_utc_at	dur.	sys.	ch.	caller	callee
1	03-03-01 00:00:00.30	1340	1	12	13905	401
4	03-03-01 00:00:00.259	3330	6	3	14663	249
6	03-03-01 00:00:00.489	1350	7	4	13905	401
7	03-03-01 00:00:00.590	2990	6	4	4266	1443
29	03-03-01 00:00:03.620	7550	2	7	13233	249
30	03-03-01 00:00:03.700	2980	9	7	16068	673
31	03-03-01 00:00:03.760	7560	1	3	13233	249
32	03-03-01 00:00:03.830	1580	2	8	13333	245
37	03-03-01 00:00:04.260	7560	7	6	13233	249
38	03-03-01 00:00:04.340	7560	6	6	13233	249

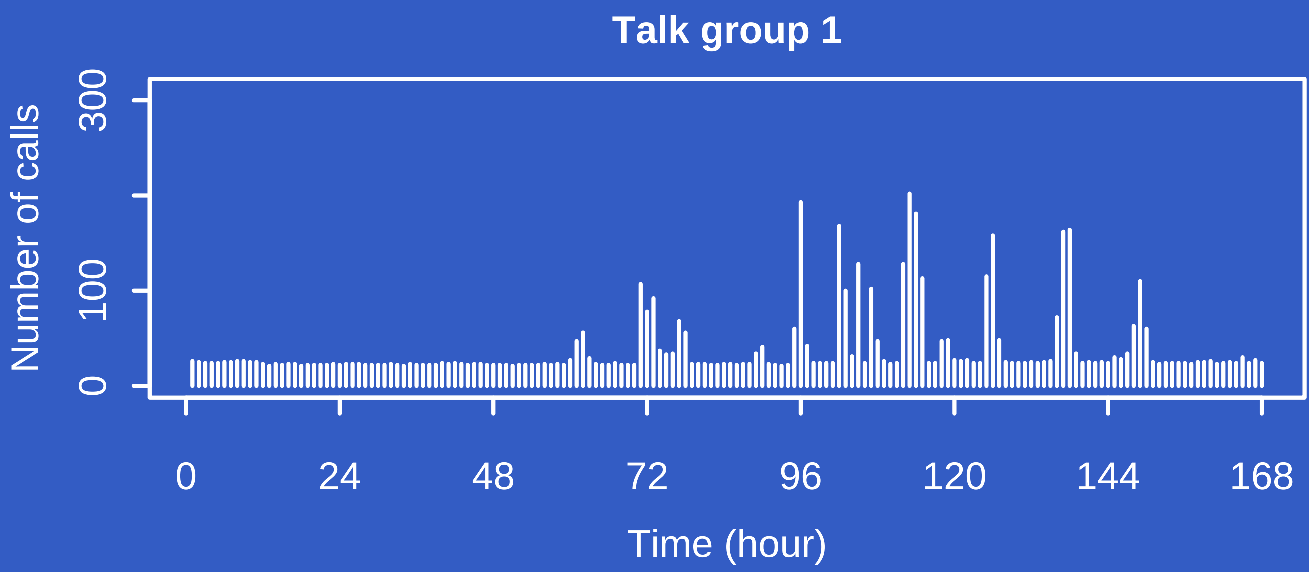
DATA CLEANING/EXTRACTION

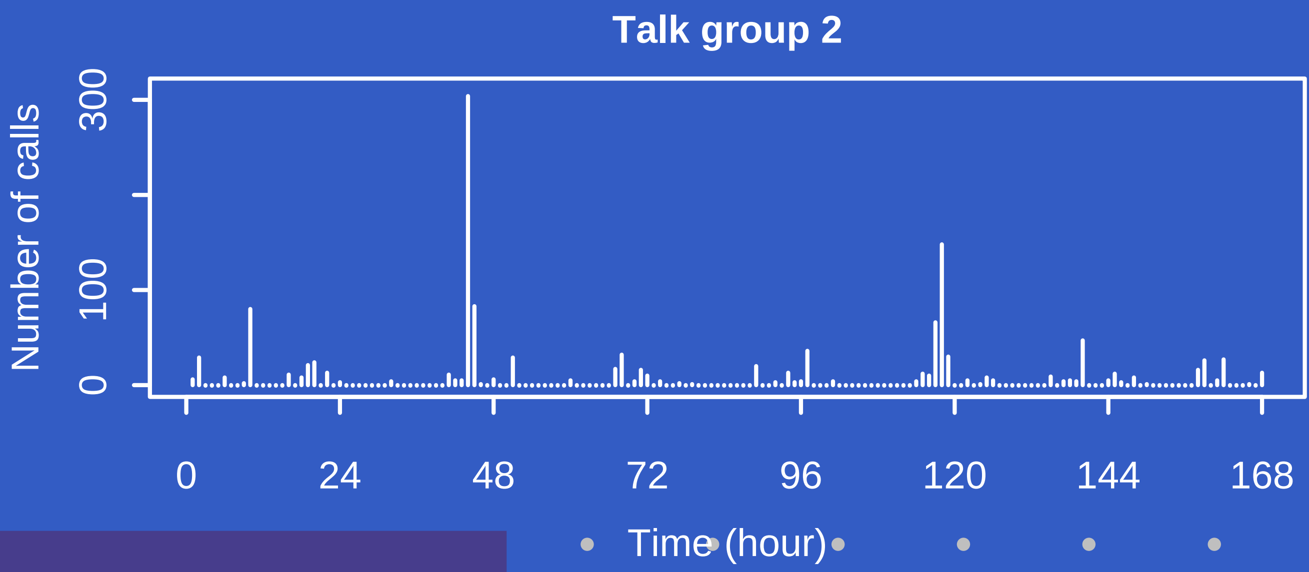
- Data cleaning: reducing database dimension, filtering outliers, removing redundant records.
- Traffic extraction: use single entry to replace multiple records for multi-system calls.
- $\sim$55% records removed after cleaning.
- $\sim$20% records remained after extraction.

CALLING BEHAVIOR PATTERN

- The basic talking unit in the E-Comm network is the talk group and the basic behavior is making a call.
- An important calling behavior pattern in the voice network is the number of calls.
- Hourly number of calls is used to represent the calling behavior pattern of talk groups.
- The collected 92 days of traffic data (2,208 hours) permitted each talk group's calling behavior pattern to be captured by the 2,208 hourly number of calls.

SAMPLE OF CALLING PATTERNS





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CLUSTERING ALGORITHMS

- Clustering analysis groups or segments a collection of objects into clusters.
- Objects within a cluster are more similar to each other than objects in distinct clusters.
- An object can be described by a set of measurements or by its relations to other objects.
- AutoClass [Cheeseman and Stutz, 1996] and K-means [Kaufman and Rousseeuw, 1990] algorithms are used to classify calling patterns of talk groups.

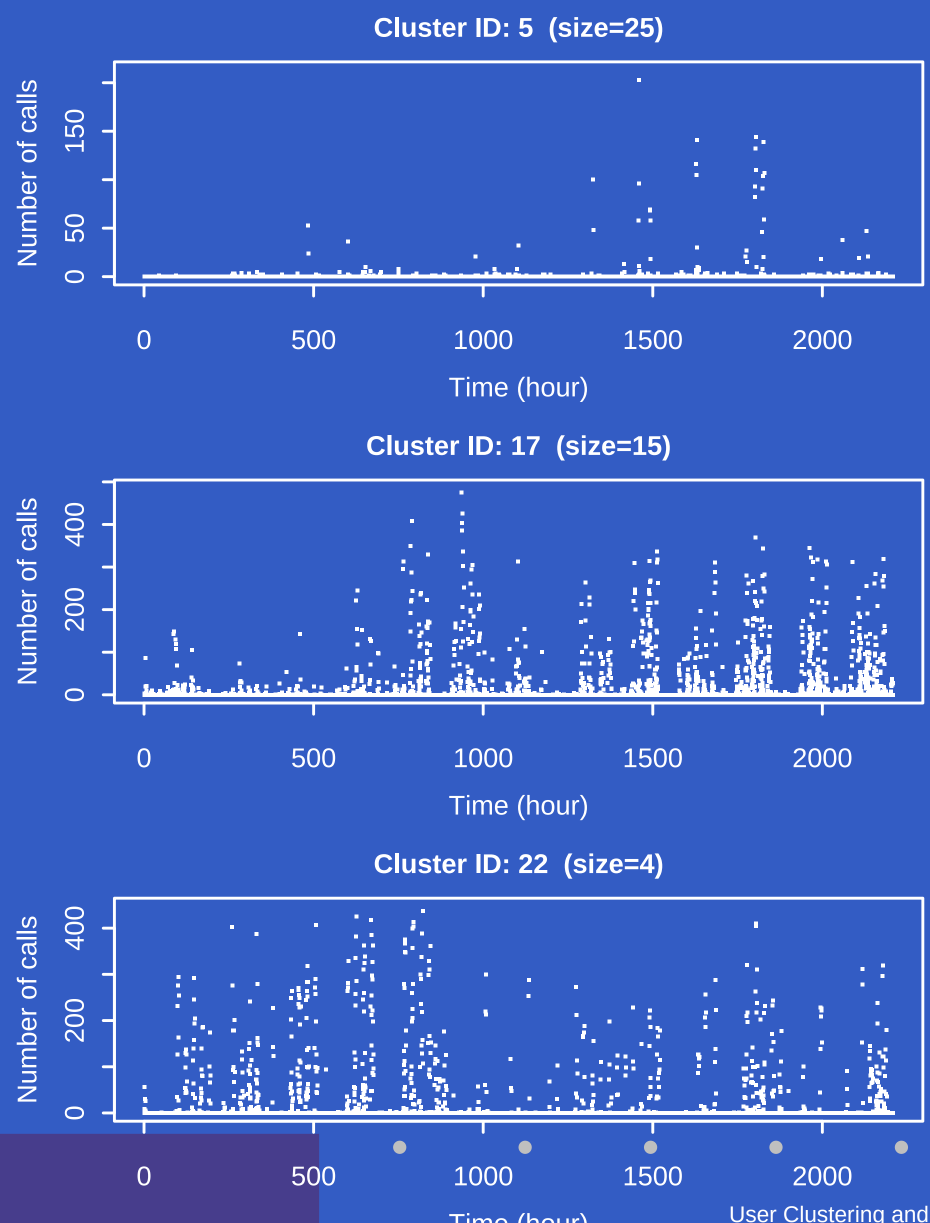
ALGORITHM: AutoClass

- An unsupervised classification tool based on the classical finite mixture model.
- Begins by creating a random classification and then manipulates it into a high probability classification through local changes.
- Repeats the process until it converges to a *local maximum*.
- Starts over again and continues for a specified number of tries.

ALGORITHM: K-means

- Based on the input parameter k, it partitions a set of n objects into k clusters so that the resulting intra-cluster similarity is high and the inter-cluster similarity is low.
- Intra-cluster similarity is measured with respect to the mean value of the objects in a cluster.
- K-means is well-known for its simplicity and efficiency.
- Own implementation and $pam()$ function in R system.

AutoClass: CLUSTERS PLOT



K-means: CLUSTER RESULTS

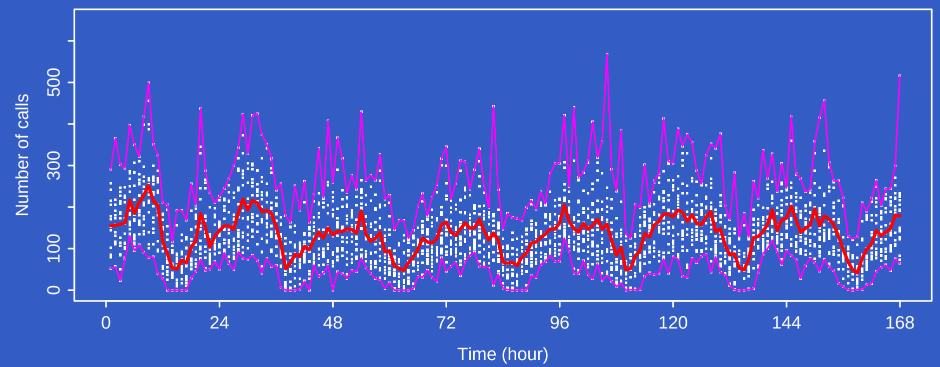
- We tested the performance of K-means for: K = 3, 6, and 16.
- The Euclidean distance was used as the distance function to measure the similarity among talk groups.
- Overall quality is defined as the minimum inter-cluster distance minus the maximum intra-cluster cluster distance.
- 3 is the best number of clusters, in terms of inter-cluster, intra-cluster distance, and overall quality.

K-means: CLUSTER RESULTS

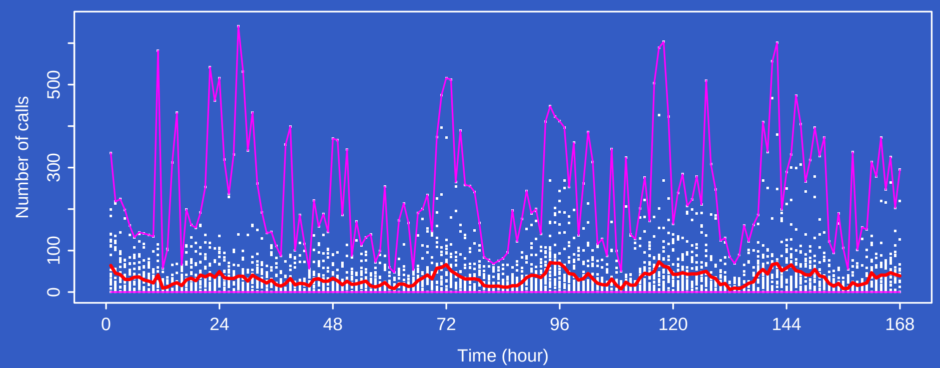
Num (K)	Sizes	Avg. intra	Avg. inter	Max. intra	Min. inter	Overall quality
3	17,31 569	1882.14	4508.38	2971.76	1626.4	-1345.36
6	13,17 22,3 34,528	2059.67	3284.52	3299.43	594.21	-2705.21
9	...	1020.08	3520.04	3065.25	808.28	-2256.96
12	...	1372.67	3582.98	3278.14	731.26	-2546.88
16	...	983.63	1815.79	3571.27	248.19	-3323.07

K-means CLUSTER PLOT

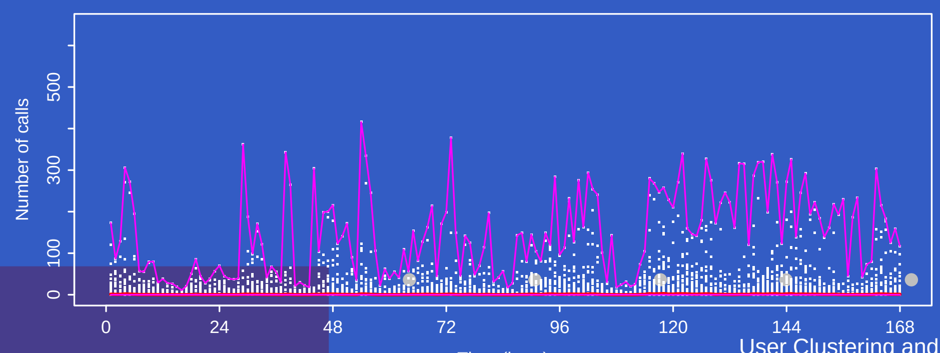
Cluster 1 (17 talk groups)



Cluster 2 (31 talk groups)



Cluster 3 (569 talk groups)



K-means CLUSTER PROPERTIES

Cluster size	Min. N.C.	Max. N.C.	Avg. N.C.	Total N.C.	Total N.C. (%)
17	0 - 6	352 - 700	94 - 208	5,091,695	59
31	0 - 3	135 - 641	17 - 66	2,261,055	26
569	0	1 - 1613	0 - 16	1,310,836	15

(N.C.: Number of calls)

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ARIMA MODELS

- The Autoregressive Integrated Moving Average (ARIMA) models were developed by Box and Jenkins in 1976.
- ARIMA notation (ARIMA (p, d, q)).
- Autoregressive model: AR(p)
  $X_t \;=\; \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + Z_t$.
- Moving average model: MA(q)
  $X_t \;=\; Z_t + \theta_1 Z_{t-1} + \ldots + \theta_q Z_{t-q}$.
- Number of differencing. (D)

SARIMA MODELS

- Seasonal ARIMA: ARIMA plus seasonal period.
- A SARIMA $(p, d, q) \times (P, D, Q)_S$ model can be represented as:

$$\phi(B^s)\phi(B)(1 - B^s)^D(1 - B)^d X_t \;=\; \theta(B^s)\theta(B)Z_t,$$

  where $\phi(B)$ and $\theta(B)$ represent the AR and MA parts, $\phi(B^s)$ and $\theta(B^s)$ represent the seasonal AR and seasonal MA parts.

- B is the back-shift operator $(B^i X_t \;=\; X_{t-i})$.

ARIMA MODEL BUILDING

- Model identification
  - (p, d, q, P, D, Q, S)
- Model estimation
  - $\phi(x)$, $\theta(x)$
- Model verification
  - residual analysis

SARIMA MODELS & NMSE

- SARIMA models $(2,0,1) \times (0,1,1)_{24}$ and $(2,0,1) \times (0,1,1)_{168}$ were selected to predict the future n hours traffic data, based on m hours past traffic data.
- Normalized mean square error $nmse$ was used to measure the prediction quality:

$$nmse(a,b) = \sum_{i=m+1}^{m+n} \frac{(a_i - b_i)^2}{(a_i - \bar{a})^2},$$

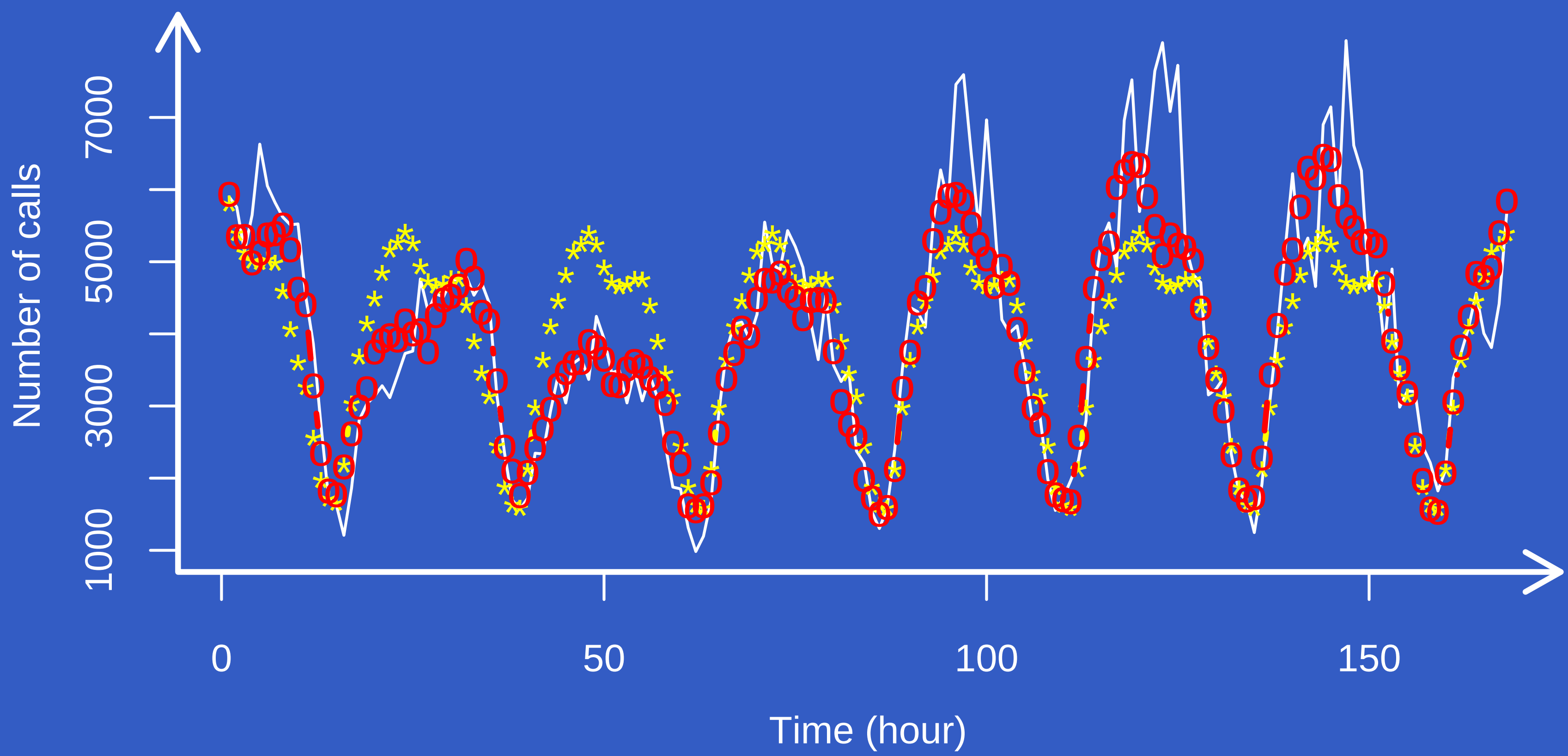
where a_i is the observed, b_i is the predicted data, and $\bar{a}$ is the mean value of a_i.

PREDICTION RESULTS

p	*d*	*q*	*P*	*D*	*Q*	*S*	*m*	*n*	*nmse*
2	0	1	0	1	1	24	1,920	24	0.1941
3	0	1	0	1	1	24	1,920	24	0.1907
2	0	1	0	1	1	24	1,680	168	0.4079
3	0	1	0	1	1	24	1,680	168	0.4081
2	0	1	0	1	1	168	1,920	24	0.0969
3	0	1	0	1	1	168	1,920	24	0.1012
2	0	1	0	1	1	168	1,680	168	0.1745
3	0	1	0	1	1	168	1,680	168	0.1748

PREDICTION VISUALIZATION

- Comparison of $(2,0,1) \times (0,1,1)_{24}$ to $(2,0,1) \times (0,1,1)_{168}$ (m:1680, n:168)



CLUSTER BASED PREDICTION

- Talk groups were partitioned into three clusters.
- SARIMA models $(2,0,1) \times (0,1,1)_{24}$ and $(2,0,1) \times (0,1,1)_{168}$ are applied for each cluster to predict the traffic.
- Predict of network traffic by aggregating the traffic predicted from three clusters of users.
- Optimize the prediction for “bad” cluster prediction.

PREDICTION RESULTS

no	(p,d,q)	(P,D,Q)	S	m	n	nmse
1	(2,0,1)	(0,1,1)	24	1680	48	1.1954
2	(2,0,1)	(0,1,1)	24	1680	48	2.4519
3	(2,0,1)	(0,1,1)	24	1680	48	0.3701
*	(2,0,1)	(0,1,1)	24	1680	48	0.6298
A	(2,0,1)	(0,1,1)	24	1680	48	0.6256
O	(2,0,1)	(0,1,1)	24	1680	48	0.4231

PREDICTION RESULTS (cont.)

no	(p,d,q)	(P,D,Q)	S	m	n	nmse
1	(2,0,1)	(0,1,1)	168	1,920	24	0.2241
2	(2,0,1)	(0,1,1)	168	1,920	24	0.3818
3	(2,0,1)	(0,1,1)	168	1,920	24	0.1163
*	(2,0,1)	(0,1,1)	168	1,920	24	0.0969
A	(2,0,1)	(0,1,1)	168	1,920	24	0.1175

PREDICTION SUMMARY

- $SARIMA(2,0,1) \times (0,1,1)_{24}$ model
  - 14% prediction based on cluster traffic beats prediction based on aggregate traffic.
  - 87% optimized prediction based on cluster traffic beats prediction based on aggregate traffic.
- $SARIMA(2,0,1) \times (0,1,1)_{168}$ model
  - 59% prediction based on cluster traffic beats prediction based on aggregate traffic.
  - None of the optimized prediction based on cluster traffic beats prediction based on aggregate traffic.

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CONCLUSIONS

- We analyzed traffic data collected from an operational trunked radio network.
- We used the K-means algorithm and AutoClass to classify network users into user clusters.
- We predicted network traffic using the SARIMA model based on aggregate user traffic and based on three user clusters.
- Some user cluster based prediction perform better than the aggregate traffic based prediction.

CONCLUSIONS - contributions

- Analyzed real-world data and problems.
- Applied clustering algorithms on real data.
- Proposed cluster based prediction method.
- Compared cluster based prediction with traditional prediction method.
- Paper published on International Symposium on Wireless Communication Systems 2004 (http://www.ieeevtc.org/iswcs04).

FUTURE WORK

- Test various clustering algorithms.
- Compare with other prediction models (HMM, FARIMA).
- Integrate with simulation tool (WarnSim).

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REFERENCE: TRAFFIC ANALYSIS

[1] D. Tang and M. Baker, “Analysis of a metropolitan-area wireless network,” in *Proc. MOBICOM 1999*, Seattle, WA, USA, Aug. 1999, pp. 13–23.

[2] L. A. Andriantiatsaholiniaina and Lj. Trajković, “Analysis of user behavior from billing records of a CDPD wireless network,” in *Proc. IEEE Workshop on Wireless Local Networks (WLN) 2002*, Tampa, FL, Nov. 2002, pp. 781–790.

[3] D. Sharp, N. Cackov, N. Lasković, Q. Shao, and Lj. Trajković, “Analysis of public safety traffic on trunked land mobile radio systems,” *IEEE J. Select. Areas Commun, Special Issue on Quality of Service Delivery in Variable Topology Networks*, vol. 22, no. 7, pp. 1197–1205, Sept. 2004.

REFERENCES: CLUSTERING

[4] P. Cheeseman and J. Stutz, “Bayesian classification (AutoClass): theory and results,” in *Advances in Knowledge Discovery and Data Mining*, U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, Eds., AAAI Press/MIT Press, 1996.

[5] L. Kaufman and P. J. Rousseeuw, *Finding Groups in Data: An Introduction to Cluster Analysis*. New York: John Wiley & Sons, 1990.

[6] J. W. Han and M. Kamber, *Data Mining: Concepts And Techniques*. San Francisco: Morgan Kaufmann Publishers, 2001.

REFERENCES: PREDICTION

[7] G. E. P. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day, 1976.

[8] The R Project for Statistical Computing [Online]. Available: http://www.r-project.org.

[9] N. K. Groschwitz and G. C. Polyzos, “A time series model of long-term NSFNET backbone traffic,” in *Proc. IEEE International Conference on Communications (ICC’94)*, vol. 3, New Orleans, LA, May 1994, pp. 1400–1404.

[10] Y. W. Chen, “Traffic behavior analysis and modeling sub-networks,” *International Journal of Network Management*, John Wiley & Sons, vol. 12, 2002, pp. 323–330.

THE END

THANKS !