Quantitative Family Data Analysis

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Overview

- I. overview of different types of family data and alternative family data analysis methods
- II. selected analyses of actual family data including
  - summary statistics
  - regression
  - analysis of variance
  - factor analysis
  - cluster analysis

Quantitative Family Data Analysis
Part I
Overview of Family Data Analysis

Family Outcomes

- outcome (dependent, response, y) variables can be the same for all family members
  - e.g., a child's behavioral problems as assessed by both the mother and the father
- or different for different family members
  - e.g., the mother's depressive symptoms and a child's behavioral problems

Number of Measurements per Family

- family data are often dyadic
  - e.g., mother's and father's assessments of family functioning
  - e.g., mother's assessments of behavioral problems for a chronically ill child and for a healthy sibling
- but can involve more than two family members
  - e.g., adolescents assessments of family functioning along with assessments from mothers and fathers
- or multiple family dimensions
  - e.g., mother's and father's assessments of behavioral problems for an ill child and for a healthy sibling

Number of Members per Family

- family data can involve different numbers of family members for different families
- e.g., a survey of parents of a chronically ill child can involve
  - single-mother, single-father, and two-parent families
  - only mothers participating, only fathers participating, or both mothers and fathers participating

Family Data Analyses

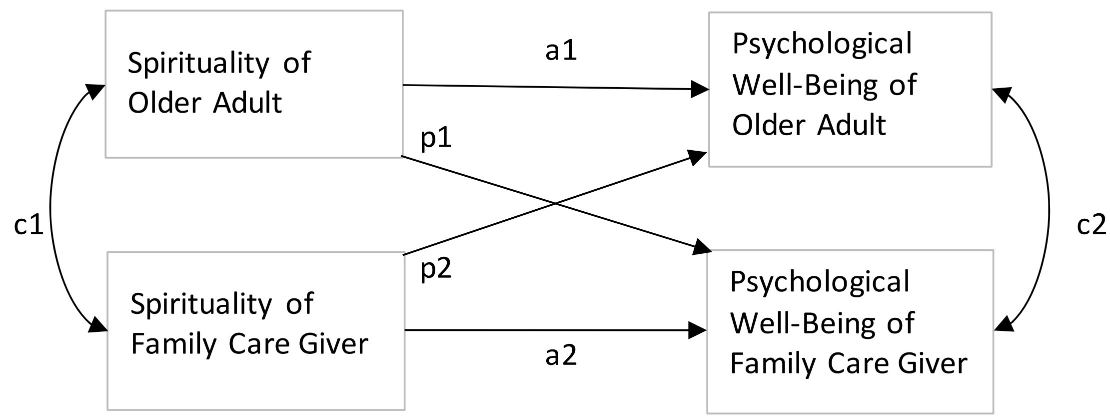
- family data need standard kinds of analyses
  - e.g., summary statistics, regression, analysis of variance, analysis of covariance
- standard methods inappropriate for analyzing the combined data for all family members
  - they assume that outcome measurements for different subjects are independent
  - but outcome measurements for members of the same family are usually correlated

Family Data Analyses

- can be more complex than for single individuals
- predictor (independent, explanatory, x) variables can provide both actor and partner effects on outcomes
  - e.g., a mother's assessment of family functioning provides
    - an actor effect for predicting her own assessment of a child's behavioral problems and
    - a partner effect for predicting her spouse's/partner's assessment of those behavioral problems
  - the Actor Partner Interdependence Model (APIM)

Campbell & Kashy (2002); Cook & Kenny (2005); Kenny, Kashy, & Cook (2006);
Rayens & Svavarsdottir (2003); Kim et al. (2011)

APIM Example



APIM model for the relationship of psychological well-being in terms of spirituality

actor effects: a1 and a2
partner effects: p1 and p2
correlations: c1 and c2

- how psychological well-being depends on spirituality
- tested using 157 Korean older adult/family care giver dyads

Kim et al. (2011)

Number of Time Points

- family data can be cross-sectional
  - i.e., measured at one point in time for multiple family members
  - analyses then need to account for the intra-familial correlation (IFC) between outcome measurements for members of the same family
- or longitudinal
  - i.e., measured at multiple points in time for multiple family members
  - analyses then need to account for temporal correlation as well as for IFC
- possible to avoid accounting for IFC

Restricting the Scope of the Study

- only study one family member
  - e.g., the mother rather than both the mother and father
- so a study of that particular individual's perspective and not really of the complete family perspective

Simplified Outcomes

- outcomes for families can be aggregated and the aggregated data analyzed with standard methods
  – e.g., averaging or differencing mother's and father's assessments of a child's behavioral problems

Uphold & Strickland (1989)

- can result in substantial loss of information on variability within families
  – and loss of data for 1-parent families with differencing
- can produce non-comparable data
  – e.g., averages for different numbers of family members have different variances and should not be analyzed with standard methods that assume constant variances

Separate Analyses

- standard methods can be applied to the data for each family member separately
  - e.g., separate averages of child behavioral problems as assessed by mothers and by fathers
  - family-related research as opposed to family research
    Feetham, 1991
- ignores the IFC, an important statistical property of the family as a unit
  - the family unit is more than just the aggregate of its individual family members
  - family data analyses should reflect this by addressing the combined data for all family members
- can also lose power for testing hypotheses
  - may be small numbers for some family members
- cannot test for differences between family members

Ignoring the IFC

- use standard methods to analyze the combined data for all family members
- treats the IFC as equal to 0
- usually very inappropriate, so results questionable
- can also have an affect on the conclusions
  – nonsignificant effects when IFC=0 can become significant when IFC is taken into consideration

Circumventing Consideration of IFC

- loss of information but not technically wrong
  - restricting the scope of the study to one family member
  - simplifying outcomes to a single value per family
    - as long as same number of family members in each family
  - conducting separate analyses of data for each family member
- incorrect with questionable results
  - ignoring the IFC and analyzing combined data for multiple family members using standard methods
  - only correct in those rare cases when IFC=0

Combined Analyses

- to test for differences in means for Y = child behavioral problems using combined data for mothers and fathers
- could try a standard regression model

$$Y = a + b \cdot \text{FATHER} + e$$

  – FATHER is an indicator for being a father
    - i.e., it equals 1 for fathers and 0 for mothers
  - where e is a mean zero random error term
  – the intercept a is the mean for mothers
  – the slope b is how much the mean for fathers differs from the mean for mothers
    - so you want to test for b=0
- problem: the errors e are independent for different subjects, which usually does not hold for mothers and fathers from the same families

Adjusting the Errors

- start with a standard regression model

$$Y=a+b\cdot FATHER+e$$

  - where e is a mean zero random error term
  - the intercept a is the mean for mothers
  - the slope b is how much the mean for fathers differs from the mean for mothers
- add in a mean zero random term u, one for each family and independent for different families

$$Y=a+b\cdot FATHER+e+u$$

- the new error terms $e'=e+u$ are correlated within families and the correlation is the IFC
- use this model to test for $b=0$

Fixed Versus Random Effects

- for the model

$$Y = a + b \cdot FATHER + e + u$$

- a and b are called fixed effects/coefficients
  - they are unknown constants
  - and $a+b \cdot FATHER$ is the fixed component of the model
- error u is called a random effect/coefficient
  - it is a random variable with mean zero and some unknown variance
  - it is called a random intercept
  - and e+u is the random component of the model
- hence this is a mixed effects model
  - i.e., containing both fixed and random effects

Multilevel (Hierarchical Linear) Model

- first level is a standard regression model

$$Y=a+b\cdot\text{FATHER}+e$$

  – intercept a and slope b are the fixed coefficients
  – but one or both are allowed to change with "subjects"
    - for family data, families are the "subjects"
- second level adjusts one or both of the model coefficients to random coefficients
- in this case, change the intercept a to a random intercept a+u (so a is the average intercept) giving

$$Y=a+u+b\cdot\text{FATHER}+e=a+b\cdot\text{FATHER}+e+u$$

  – can also adjust b to b+v
- correlation for $e'=e+u$ called the intraclass correlation coefficient (ICC) in general but is IFC for family data

Singer (1998)

Linear Mixed Model

$$Y=a+b\cdot FATHER+e'$$

- has fixed component $a+b\cdot FATHER$ modeling means
- and random component e' modeling variances/ correlations (or equivalently, covariances)
- random errors e' are chosen to be independent for different families but correlated for different members of the same family
- $e'=e+u$ generated by a random intercept works for any number of family members and produces
  - same variance for all family members and
  - same correlation for all pairs of distinct family members
  - so it is called compound symmetry (CS)

Adjustments to Random Component

- compound symmetry (CS) is the model used in standard repeated measures analyses
- same variances for all family members might be too simplistic for family data
  - can be changed to heterogeneous variances (CSH)
- same correlations might be too simplistic for data based on more than two family members
  - can be changed to unstructured (UN) correlations with different IFCs for each pair of family members
- unstructured (UN) correlations with heterogeneous variances is model used in multivariate ANOVA

Adjustments to Fixed Component

- should account for differences in means for
  - different types of family members
    - e.g., fathers and mothers
  - different types of families
    - e.g., one-parent versus two-parent families
  - different numbers of participating family members
    - e.g., only mother, only father, or both participating
  - can do this with indicator variables like FATHER
- can also add predictor variable(s) X
- and interactions like FATHER·X

Structural Equation Modeling (SEM)

- has been used to model family data for some time
  Thomsom & Williams (1982); Clarke (1995)
- in a standard regression model
  - only the outcome Y is measured with error
  - predictors X are treated as measured without error
- SEM allows predictors to be measured with or without error
- very complex relationships can be more readily modeled with SEM than with linear mixed modeling
  - but otherwise either are as effective

Types of Outcomes

- linear mixed models apply to continuous family outcomes that can be treated as normally distributed
  - e.g., depressive symptoms for family care givers/ receivers
- categorical family outcomes require generalized linear modeling
  - e.g., being depressed (having a high level of depressive symptoms) vs. not for family care givers/receivers
  - can use generalized estimating equations (GEE) techniques to account for IFC

Data Structure

- family data are often stored as one record per family with separate variables containing measurements for different family members (called wide format)
- then they need to be restructured for analysis (called long format)

from

FAMID	YMOTHER	YFATHER
1	10	12
2	15	10
...		

to

FAMID	FATHER	Y
1	0	10
1	1	12
2	0	15
2	1	10
...		

Longitudinal Data

- the multilevel model starts with a standard regression model in time T

$$Y=a+b\cdot T+e$$

- and replaces the slope b by a random slope b+v where v has mean zero (so b is the average slope) and is independent across different subjects but correlated within times for the same subject

$$Y=a+(b+v)\cdot T+e=a+b\cdot T+v\cdot T+e$$

- new error terms $e'=v\cdot T+e$ are correlated within times for the same subject
- a type of random coefficients model

Longitudinal Data

- alternately, the standard regression model in time T

$$Y=a+b\cdot T+e$$

- can be adjusted by also replacing the fixed intercept a by a random intercept a+u where u has mean zero (so a is the average intercept) and is independent across subjects but correlated within times for each subject

$$Y=a+u+(b+v)\cdot T+e=a+b\cdot T+u+v\cdot T+e$$

- new error terms $e'=u+v\cdot T+e$ are correlated within times for the same subject

Linear Mixed Model

$$Y=a+b\cdot T+e'$$

- where the error terms e' have mean zero, are independent across different subjects and correlated within times for the same subjects
- $e'=v\cdot T+e$ and $e'=u+v\cdot T+e$ are cases generated by multilevel modeling
- autoregression is a common alternative for e'
  - treats correlations as weakening the farther apart outcomes are in time
  - cannot be generated by a random coefficients model

Longitudinal Family Data

- multilevel model starts with a standard regression model in time T and FATHER

$$Y=a+b_1\cdot T+b_2\cdot FATHER+e$$

- and replaces the fixed intercept a, slope b_1 for T, and slope b_2 for FATHER by random coefficients $a+u$, b_1+v_1, and b_2+v_2 (or any subset of these)

$$Y=a+u+(b_1+v_1)\cdot T+(b_2+v_2)\cdot FATHER+e$$
$$=a+b_1\cdot T+b_2\cdot FATHER+u+v_1\cdot T+v_2\cdot FATHER+e$$

- new error terms $e'=u+v_1\cdot T+v_2\cdot FATHER+e$ are correlated within members of the same family and within times for those family members

Lyons & Sayer (2005)

Linear Mixed Model

$$Y = a + b_1 \cdot T + b_2 \cdot FATHER + e'$$

- error terms e' are independent across different families and correlated within members of the same family and within times for those family members
- $e' = u + v_1 \cdot T + v_2 \cdot FATHER + e$ is the case generated by the multilevel or random coefficients model
  - a regression model in random coefficients
- two-dimensional correlation structures are alternatives for e'
  - e.g., unstructured correlations within family members along with autoregressive correlations within times

Types of Outcomes

- linear mixed models only apply to continuous longitudinal family outcomes that can be treated as normally distributed
  - e.g., depressive symptoms for family care givers/ receivers over multiple time points
- categorical longitudinal family outcomes require generalized linear mixed modeling
  - e.g., depressed (high levels of depressive symptoms) vs. not for family care givers/receivers over multiple time points
  - GEE as usually implemented cannot account for both IFC and temporal correlation

Summary for Part I

- family data
  - can involve different numbers of family members and different types of families
  - can be cross-sectional or longitudinal
- family outcomes
  - can be the same or different for different family members
  - can be continuous or categorical
  - can be analyzed with mixed models accounting for
    - differences in means and standard deviations
    - IFC and possibly also temporal correlation
    - dependence on one or more predictor variables

Quantitative Family Data Analysis
Part II
Selected Family Data Analyses

Child Adaptation Data

- cross-sectional study of parents of a child with a chronic condition (e.g., diabetes, Crohn's disease)
- available measures
  - Y = child adaptation in intensity of behavioral problems (Eyberg Child Behavioral Inventory)
    - larger values mean more problems and so worse child adaptation
  - FF = family functioning (McMaster Family Assessment Device)
    - larger values mean poorer levels of family functioning
- 324 two-parent families
  - with mothers participating for all families
  - with fathers also participating for 145 (44.8%) of the families

Knafl et al. (2009), JFN methods paper

Summary Statistics - Child Adaptation

$$Y=a+b_1 \cdot FATHER+b_2 \cdot MOMONLY+e'$$

FATHER is 1 if a father and 0 if a mother

MOMONLY is 1 if a mother without a participating father and 0 if a mother with a participating father or a father

- e' = errors with mean zero, independent across different families, correlated within families, and with different variances for mothers/fathers (CSH)
- a is mean child adaptation for mothers with participating fathers
- b_1 is change in mean for fathers compared to mothers of the same families
- b_2 is change in mean for mothers without participating fathers compared to mothers with participating fathers

Summary Statistics - Child Adaptation

$$Y=a+b_1 \cdot FATHER+b_2 \cdot MOMONLY+e'$$

- estimated mean child adaptation a for mothers with participating fathers was 87.5
- estimated change in mean b_1 for fathers compared to mothers of the same families was 2.8 and was not significant ($p=0.16$)
- estimated change in mean b_2 for mothers without participating fathers compared to mothers with participating fathers was –1.5 and was not significant ($p=0.65$)
- estimated standard deviations were close at 29.0 and 28.4 for mothers and fathers, respectively
- estimated IFC was 0.65 and significant ($p<0.01$)
- mean child adaptation did not change with type of family and type of family member but the IFC was substantial

Adaptation vs. Family Functioning

$$Y=a+b_1 \cdot FATHER+b_2 \cdot MOMONLY+b_3 \cdot FF+e'$$

- FF = family functioning
- e' = errors with mean zero, independent across different families, correlated within families, and with different variances for mothers/fathers (CSH)
- $a+b_3 \cdot FF$ is how mean child adaptation changes with family functioning for mothers with participating fathers
- b_1 is how much this relationship is shifted up/down for fathers compared to mothers of the same families
- b_2 is how much this relationship is shifted up/down for mothers without participating fathers compared to mothers with participating fathers

Adaptation vs. Family Functioning

$$Y=a+b_1\cdot FATHER+b_2\cdot MOMONLY+b_3\cdot FF+e'$$

- the estimated slope b_3 for family functioning FF was 16.4 and was significant ($p<0.01$)
  - mean child adaptation got worse (larger values or more behavioral problems) with poorer family functioning (larger values)
- this relationship was not significantly shifted for fathers ($p=0.08$) or for mothers without participating fathers ($p=0.57$)
- estimated standard deviations were close (27.8 for mothers and 27.2 for fathers)
- estimated IFC was substantial at 0.63 ($p<0.01$)

Father Effect

- perhaps the very nonsignificant MOMONLY effect ($p=0.57$) masked a significant FATHER effect
- the p-value for the test of zero slope for FATHER changed from nonsignificant ($p=0.08$) to significant ($p=0.04$) with the removal of MOMONLY
  - inclusion of MOMONLY did mask significant effect to FATHER
  - estimate of b_1 was > 0, so fathers considered child adaptation to be worse (more behavioral problems) than mothers
- in general, effects to family variables need to be considered in analyses since the mean outcome might change with those family variables
- but, in general, there is also a need to investigate reduced models in order to identify significant effects
- also need to consider alternative covariance structures
- so model selection criteria are needed

Penalized Likelihood Criteria (PLCs)

- for model selection
- likelihood adjusted by a penalty factor
  - likelihood changes with the distribution for data
  - likelihood is based on the multivariate normal density for linear mixed models
- formulated so that smaller scores indicate better models
- Akaike Information Criterion (AIC) has penalty factor based on the number of model parameters
- Schwarz's Bayesian Information Criterion (BIC) has penalty factor based on the number of observations and the number of model parameters
- AIC and BIC do not always agree on which is the better model

Evaluation of Variances

- AIC/BIC agree that, for the child adaptation data, homogeneous variances are preferable to heterogeneous variances
- and conclusions about fixed effects are the same
  - effects to FATHER and FF (family functioning) were significant under both variance alternatives
- not always the case and so it is important to consider alternatives for variances
  - and for correlations when appropriate

Summary of Adaptation Analyses

- as expected from the literature poorer family functioning corresponded with worse adaptation of a child to a chronic condition
- this relationship was the same for mothers with and without participating fathers
  - based on MOMONLY
- but was shifted up for fathers compared to mothers
  - but only after removing the nonsignificant MOMONLY effect
- variances did not differ much with family member
  - and were reasonably treated as homogeneous
  - but in general this will not be the case
- the IFC was substantial
  - it was important to account for this correlation
  - treating it as zero would have been very inappropriate

Impact of IFC

- when IFC is treated as equal to 0
- by modeling the data using a standard regression model in FATHER and FF
- the slope for FATHER is no longer significant ($p=0.10$)
- ignoring the correlation/covariance in family data can have an impact on the conclusions
  - usually results in a loss of power for identifying significant fixed effects

Other Family Effects

- if single mothers are also included in the study, can use the following

$$Y = a + b_1 \cdot FATHER + b_2 \cdot MOMONLY + b_3 \cdot FF + b_4 \cdot SNGLMOM + e'$$

- where SNGLMOM is 1 if a single mother and 0 otherwise
- single fathers and families with only participating fathers can be handled similarly

Family Data Mediation/Moderation

- can be addressed with regression models for means as for non-family data
- but need to use mixed modeling to account for IFC and possibly heterogeneous variance
- also need to adjust means for effects to type of family member and type of family
  - but may need to remove some of these if very nonsignificant since they may mask the mediation/moderation effects

Family Instrument Development Data

- cross-sectional study of parents of a child with a chronic condition to develop a survey instrument for measuring aspects of family management of the chronic condition
- 65 items were developed based on the Family Management Style Framework
- 579 parents from 417 families were surveyed including
  - 414 mothers with 349 (84.3%) partnered and 65 (15.7%) single
  - 165 fathers with mothers participating for all but 3 fathers
- only about 1% of the item values were missing, so these were imputed

Knafl et al. (2011); a subset of these data was analyzed earlier

Factor Analysis

- factor analysis models assume independence for item responses for different subjects
  - and so should not be applied to combined item responses for mothers and fathers from the same families
- 8 of the 65 items addressed parental mutuality which only applies to partnered parents
  - so single mothers responded to only 57 of the items
  - standard factor analysis procedures drop such partial sets of item responses
  - imputation of parental mutuality items not sensible for single mothers
- so we factor analyzed only the item responses for the 349 partnered mothers
  - since we considered mothers the primary family member

Family Management Measure (FaMM)

- 6 scales were produced based on 53 of the 65 items
  - child's daily life
  - condition management ability
  - condition management effort
  - family life difficulty
  - parental mutuality (only for partnered parents)
  - view of condition impact
- special methods were used to generate the scales that also allowed us to justify that those scales were appropriate for use by fathers and by single mothers
- internal consistency reliability, test-retest reliability, and construct validity were based on data for all parents using specialized linear mixed models accounting for IFC and differences for family members and for types of families
- Knafl et al. (2012)

Family Functioning Data

- from a cross-sectional study of parents of a child with a genetic condition
  – including PKU, CF, neurofibromatosis, sickle cell disease, thalassemia, hemophilia, and Marfan's syndrome
- two available measures of family functioning
  – Y_1 = satisfaction (Family APGAR)
    - larger values mean more satisfied with family life
  – Y_2 = hardiness (Family Hardiness Index)
    - larger values mean higher levels of hardiness (strength and durability)
- 52 two-parent families with both parents participating

Knafl et al. (2007)

Family Functioning Clusters

- wanted to classify family functioning for these 52 families
  - using both Y_1 = satisfaction and Y_2 = hardiness for both mothers and fathers
- not appropriate to cluster the 2·52=104 vectors (Y_1,Y_2) for mothers and fathers combined
  - clustering methods allow for correlation within a vector for the same subject, but treat vectors as independent across subjects
- can cluster the 52 vectors $(Y_{1,mother},Y_{2,mother})$ for mothers separately from the 52 vectors $(Y_{1,father},Y_{2,father})$ for fathers
  - but this will not take into account similarities and differences for mothers and fathers of the same families
- so we clustered the 52 combined vectors for both parents
  - i.e., $(Y_{1,mother},Y_{2,mother},Y_{1,father},Y_{2,father})$

Generated Clusters

- Ward's method generated 5 family functioning types
  - well-adapted families (21 or 40.4%) with both parents tending to rate both satisfaction and hardiness as high
  - discrepant families (10 or 19.2%) with mothers tending to rate satisfaction and hardiness as high but with fathers tending to rate them both as moderate
  - diminished families with both parents tending to rate satisfaction and/or hardiness as moderate
    - with mothers diminished more in satisfaction (8 or 15.4%)
    - or with mothers diminished more in hardiness (11 or 21.2%)
  - compromised families (2 or 3.8%) with both parents tending to rate satisfaction and hardiness as low

Validity of the Clusters

- validated the clusters using
  - parental quality of life (QOL) (Quality of Life Index)
  - child functional status (Functional Status II)
  - reduced clusters to 3 so no sparse clusters
    - by combining the diminished and compromised clusters into a single diminished/compromised cluster
- considered ANOVA models for these variables
  - with main effects to type of parent and to cluster as well as an interaction effect to type of parent and cluster
    - expected means to change with clusters
  - using linear mixed models with errors correlated within families and independent across different families

Cluster Validity Results

- mean QOL changed significantly with cluster ($p<0.01$) and with the interaction ($p=0.01$) but not with type of parent ($p=0.06$)
  - a post hoc analysis revealed that (joint $p<0.05$)
    - mean QOL was lower for diminished/compromised parents than for well-adapted parents
    - with the difference being greater for diminished/compromised mothers than for diminished/compromised fathers
    - and was lower for fathers than mother of discrepant families

Cluster Validity Results

- mean child functional status changed significantly with cluster ($p=0.01$) but not with type of parent ($p=0.37$) or with the interaction ($p=0.47$)
  - a post hoc analysis revealed that (joint $p<0.05$)
  - child functional status was lower for diminished/compromised families than for the well-adapted and the discrepant families
- results for QOL and child functional status supported the validity of the clusters

Issues in Clustering Family Data

- these analyses used data from families for which there were two participating parents
  - data from families with only mothers participating were not used in the analyses
  - since hierarchical clustering procedures (e.g., SAS PROC CLUSTER) supporting Ward's method drop partial vectors
- possible to include families with partial vectors
  - k-means clustering
  - automatically adjusts the computation of distances between vectors of different sizes

Summary of Parts I-II

- have provided an overview of family data and the kinds of analyses they require
- have also provided examples of actual analyses of selected family data
- methods are available for analyzing the combined data for family members that account for IFC in most situations
  - factor analysis was the exception
- in many situations, these analyses require only fairly straightforward linear mixed models
  - but some cases require more sophisticated techniques and the assistance of a statistician
- however, it is important to address IFC in analyses of family data

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