Two novel approaches for photometric redshift estimation based on SDSS and 2MASS databases *

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Abstract We investigate two training-set methods: support vector machines (SVMs) and Kernel Regression (KR) for photometric redshift estimation with the data from the Sloan Digital Sky Survey Data Release 5 and Two Micron All Sky Survey databases. We probe the performances of SVMs and KR for different input patterns. Our experiments show that the more parameters considered, the accuracy doesn’t always increase, and only when appropriate parameters chosen, the accuracy can improve. Moreover for the two approaches, the best input pattern is different. With various parameters as input, the optimal bandwidth is dissimilar for KR. The rms errors of photometric redshifts based on SVM and KR methods, are less than 0.03 and 0.02, respectively. Finally the strengths and weaknesses of these techniques are summarized. Compared to other methods of estimating photometric redshifts, they show their superiorities, especially KR, in terms of accuracy.

Key words: galaxies: distances and redshifts - galaxies: general - methods: data analysis - techniques: photometric

1 INTRODUCTION

Photometric redshifts have been regarded as the most promising tool in studying the formation and evolution of galaxies and the large scale structure of the universe, especially when the spectra of faint objects are difficult to obtain. The photometric redshift technique translates observables such as flux and apparent color to the corresponding
intrinsic properties of absolute luminosity and rest-frame color. The idea behind the photometric redshift technique is to measure the redshifts of galaxies and AGN based on available multi-wavelength photometry. Photometric redshift techniques can be traced back to Baum (1962) who used nine medium-wide filters to detect the 4000Å in galaxies. For example, the predicted redshift of the C10925 galaxies by this technique is $z = 0.19$, which agrees closely with the known spectroscopic value of $z = 0.192$. Subsequent implementations have been made by Koo (1985) using four broad-band photographic filters, Loh and Spillar (1986) using CCDs along with 6 medium-band filters, and Xia et al. (2002) using CCD photometries of BATC 15 medium-band filters. In the last two decades, some well-defined statistical techniques have become increasingly popular in predicting photometric redshifts.

There are two kinds of different photometric redshift approaches in the astronomical literature: the template fitting whose templates are derived from synthetic (e.g. Bruzual, Charlot 1993) or empirical template spectra (e.g. Coleman, Wu, Weedman 1980), and the empirical training set method which constructs a direct empirical correlation between color and redshifts. For template fitting one, according to the known redshift and galaxy type, some templates are constructed in advance. By minimizing the standard $\chi^2$ to fit the observed photometric data with a set of spectral templates, this method can be applied beyond redshift limit. Although it is easy to implement, the accuracy of this approach strongly depends on the templates. The essence of training set approach is to derive a function between redshift and photometric data by using a large and representative training set of galaxies for which both photometry and redshift are known, and then use this function to estimate the redshifts of objects with unknown redshifts. In the last few years, a large number of training set methods have been developed and used (Way, Srivastava 2006). For example, linear or non-linear fitting (Brunner et al. 1997; Wang, Bahcall, Turner 1998; Budavari et al. 2005); support vector machines (SVMs, Wadadekar 2005); artificial neural network (ANNs, Firth, Lahav, Somerville 2003, Ball et al. 2004, Collister, Lahav 2004, Vanzella et al. 2004, Li et al. 2006); instance-based learning (Csabai et al. 2003; Ball et al. 2007).

The main advantage of SVMs over ANNs is that requires less effort in training, and no danger of overfitting. SVMs simplify the decision of the optimal networks by replacing the choice of architecture problem with one of choice of kernel (Wadadekar 2005). The strength of instance-based learning methods is that they needn’t training, but implement their predictions directly on (training) data that has been stored in the memory. In general, they store all the training data in the memory during the learning phase, and defer all the essential computation until the prediction phase. Kernel regression (KR) belongs to the instance-based learning family. Based on the merits of SVMs and KR, we adopt these two methods to predict photometric redshifts of galaxies.
In this paper we explore two approaches: support vector machines (SVMs) and kernel regression (KR) to estimate redshifts of galaxies with photometric data from SDSS and 2MASS databases. The structure of this paper is as follows: Section 2 illustrates the data used in the study. Section 3 describes the principles of SVMs and KR. Section 4 gives the results and discussion. Finally the conclusions are summarized in Section 5.

2 DATA

The data used in this paper is from Sloan Digital Sky Survey (SDSS) and Two Micron All Sky Survey (2MASS) catalogs. The process of data preprocessing has been done by VO_DAS, which is a data accessing system of Virtual Observatory of China. The general information of SDSS and 2MASS is shown as follows.

The Sloan Digital Sky Survey (SDSS, York et al. 2000) is an astronomical survey project, which covers more than a quarter of the sky, to construct the first comprehensive digital map of the universe in 3D, using a dedicated 2.5-meter telescope located on Apache Point, New Mexico. In its first phase of operations, it has imaged 8,000 square degrees in five bandpasses \((u, g, r, i, z)\) and measured more than 675,000 galaxies, 90,000 quasars and 185,000 stars. In its second stage, SDSS will carry out three new surveys in different research areas, such as the nature of the universe, the origin of galaxies and quasars and the formation and evolution of the Milky Way.

The Two Micron All Sky Survey (2MASS, Cutri et al. 2003) uses two highly-automated 1.3-m telescopes, one is at Mt. Hopkins, Arizona and the other locates at CTIO, Chile. Each telescope is equipped with a three-channel camera, each channel consisting of a 256x256 array of HgCdTe detectors, capable of observing the sky simultaneously at \(J\) (1.25 \(\mu\)m), \(H\) (1.65 \(\mu\)m), and \(K_s\) (2.17 \(\mu\)m), to a 3\(\sigma\) limiting sensitivity of 17.1, 16.4 and 15.3 mag in the three bands. Jarrett et al. (2000) has more detailed information on the extended source catalog.

We select all galaxies with known spectra redshifts from SDSS Data Release 5, and then cross-match the data with 2MASS extended source catalog within a search radius of 3 times the SDSS positional errors. After cross-matching, we generate about 150,000 galaxies. From these galaxies, we selected the objects satisfying the following criteria: 1) the spectroscopic redshift confidence must be equal to or greater than 0.95; 2) redshift warning flag is 0; 3) \(r < 17.5\). With these qualifications, a sample of 62,083 galaxies is obtained. Table 1 describes the broadband filters and their wavelength range from SDSS and 2MASS catalogs.
Table 1 Survey filters and characteristics

| Bandpass | Survey | λ_{eff}(Å) | Δλ(Å) |
|----------|--------|------------|-------|
| u        | SDSS   | 3551       | 600   |
| g        | SDSS   | 4686       | 1400  |
| r        | SDSS   | 6165       | 1400  |
| i        | SDSS   | 7481       | 1500  |
| z        | SDSS   | 8931       | 1200  |
| J        | 2MASS  | 12500      | 1620  |
| H        | 2MASS  | 16500      | 2510  |
| Ks       | 2MASS  | 21700      | 2620  |

3 MODEL SELECTION

3.1 Support Vector Machines

The foundation of Support Vector Machines (SVMs) has been developed by Vapnik (1995). SVMs were developed to solve the classification problem, but recently they have been extended to the domain of regression problems. The regression problem of SVMs is achieved by using an alternative loss function, which must be modified to include a distance measure. The SVM task usually involves with training and testing data which consist of some data instances. Each instance in the training set contains one “target value” and several “attributes”. The goal of SVMs is to produce a model which predicts target value of data instances in the testing set which are given only the attributes.

Given a training set of training pairs (x₁,y₁),..,(xₙ,yₙ), xᵢ ∈ Rⁿ, yᵢ ∈ R, with a linear function,

\[ f(x) = \langle \omega, x \rangle + b, \quad (1) \]

The optimal regression function is given by the minimum of the functional,

\[ \phi(\omega, \zeta) = \frac{1}{2} \omega . \omega + C \sum_i (\zeta_i^- + \zeta_i^+), \quad (2) \]

Using a quadratic loss function,

\[ L_{quad}(f(x) - y) = (f(x) - y)^2, \quad (3) \]

the solution is given by,

\[
\max_{\alpha, \alpha^*} W(\alpha, \alpha^*) = \max_{\alpha, \alpha^*} - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) < x_i, x_j > \\
+ \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) y_i - \frac{1}{2C} \sum_{i=1}^{l} (\alpha_i^2 + (\alpha_i^2)^2), \quad (4)
\]

the resultant optimization problems is,

\[
\min_\beta \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \beta_i \beta_j < x_i, x_j > - \sum_{j=1}^{l} \beta_j y_i + \frac{1}{2C} \sum_{i=1}^{l} \beta_i^2 \quad (5)
\]
with constraints,
\[ \sum_{i=1}^{l} \beta_i = 0. \] (6)

To generalize to non-linear regression, we replace the dot product with a kernel function. More information can be found in Steve’s tutorial (1998). In our work, we adopt the Gaussian kernel function.

SVMs have been widely used in the area of machine learning due to its excellent generalization performance, such as handwritten digit recognition and face detection. In astronomy, SVMs have been applied to identifying red variables (Williams et al. 2004), clustering astronomical objects (Zhang, Zhao 2004), and classifying AGN from stars and normal galaxies (Zhang, Cui, Zhao 2002).

Several software implementations of the SVM algorithm are accessible on the web. Due to their robustness, the ability of handling large amounts of data, and the regression time, we use SVMLight for our study. SVMLight is fast optimized SVM algorithm, which is implemented in C language. It can deal with many thousands of support vectors, handle hundreds/thousands of training examples, and provide several standard kernel functions. The details about SVMLight can be found at http://www.cs.cornell.edu/People/tj/svmlight/.

### 3.2 Kernel Regression

Kernel regression (KR) belongs to the family of instance-based learning algorithms (Watson 1964; Nadaraya 1964), which simply store some or all of the training examples and do not perform any kind of generalization of the given samples and “delay learning” till prediction time. Given a query point \( x_q \), a prediction is obtained using the training samples that are “most similar” to \( x_q \). Similarity is measured by means of a distance metric defined in the hyper-space of \( V \) predictor variables. Kernel regressors obtain the prediction for a query point \( x_q \), by a weighted average of the \( y \) values of its neighbors. The weight of each neighbor is calculated by a function of its distance to \( x_q \) (called the kernel function). These kernel functions give more weight to neighbors that are nearer to \( x_q \). The notion of neighborhood (or bandwidth) is defined in terms of distance from \( x_q \).

The prediction for query point \( x_q \) is obtained by

\[
y_q = \frac{\sum_{i=1}^{N} K\left(\frac{D(x_i, x_q)}{h}\right) \times y_i}{\sum_{i=1}^{N} K\left(\frac{D(x_i, x_q)}{h}\right)}
\] (7)

where \( D(.) \) is the distance function between two instances; \( K(.) \) is a kernel function; \( h \) is a bandwidth value; \( (x_i, y_i) \) are training samples. In this paper, we use Euclidian distance and Gaussian kernel function. \( x_i \) is the feature for each training sample, \( y_i \) is the spectroscopic redshift for each training set sample, \( y_q \) is the redshift of each query sample.
One important design decision when using kernel regression is the choice of the bandwidth \( h \). The larger \( h \) results in the flatter weight function curve, which indicates that many points of training set contribute quite evenly to the regression. As the \( h \) tends to infinity, the predictions approach the global average of all points in the database. If the \( h \) is very small, only closely neighboring data points make a significant contribution. If the data are relatively noisy, we expect to obtain smaller prediction errors with a relatively larger \( h \). If the data are noise free, then a small \( h \) will avoid smearing away fine details in the function. There exists mature algorithms for choosing the bandwidth for kernel regression that minimize a statistical measure of the difference between the true underlying distribution and the estimated distribution. Usually bandwidth selection in regression is done by cross-validation (CV).

In this work, we chose the bandwidth using cross-validated method. Cross-validation is the statistical method of dividing a sample of data into subsets such that the analysis is initially performed on a single subset, while the other subset(s) are retained for subsequent use in confirming and validating the initial analysis. \( M \)-fold cross-validation is one important cross-validation method. The data are divided into \( m \) subsets of (approximately) equal size. Each time, one of the \( m \) subsets is used as the test set and the other \( m - 1 \) subsets are put together to form a training set for a given bandwidth. Then the average error across all \( m \) trials is computed (Zhang, Zhao 2007). Here we adopt 10-fold cross-validation for the bandwidth choice dividing the samples into 10 subsets, then 9 subsets of 10 subsets are taken as training set and the rest subset as testing set for ten times. The optical bandwidth is indicated by the bandwidth with the minimum of average errors. In Table 2, we apply KR with 7-color \((u-g, g-r, r-i, i-z, z-J, J-H, H-Ks)\) and spectra redshifts as an input pattern, taking it as an example to illustrate the relationship between bandwidth \((h)\) and cross-validated value \((CV)\). It is obvious that the optimal bandwidth \( h \) is 0.045 when cross-validated value arrives at the minimum 4.33.

| \( h \)       | 0.015 | 0.02  | 0.025 | 0.03  | 0.035 | 0.04  | 0.045 | 0.05  | 0.055 | 0.06   |
|--------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| CV\((\times 10^{-5})\)| 4.77  | 5.03  | 4.86  | 4.64  | 4.45  | 4.35  | 4.33  | 4.35  | 4.41  | 4.77  |

### 4 RESULT AND DISCUSSION

One advantage of the empirical training set approach to photometric redshift estimation is that additional parameters can be easily incorporated. More parameters (e.g. \( petro50_r, petro90_r, fracDeV_r, \) etc.) may be taken as inputs. In order to study which parameters influence the accuracy of predicting photometric redshifts, we probe different
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input patterns to estimate photometric redshifts. We randomly divide the sample into
two parts: 41,388 for training and 20,695 for test, and apply them to train and test kernel
regression (KR) and support vector machines (SVMs). The rms deviations of predicting
photometric redshifts with KR and SVMs for different situations are listed in Table 3.

When using SVMs to estimate photometric redshifts, the performances of colors are
the best of all cases. The result based on 4-color input pattern \((u-g, g-r, r-i, i-z)\) has
the same best accuracy \(\sigma_{\text{rms}}=0.0273\) as that based on 7-color input pattern
\((u-g, g-r, r-i, i-z, z-J, J-H, H-Ks)\). The accuracy with seven colors and \(r\) magnitude is better
than that with four colors and \(r\) magnitude, and than that with seven magnitudes. The
performance taking five magnitudes as input is not as well as that of seven magnitudes.
Since the accuracy with four colors is best, we consider more parameters besides four
colors to probe whether the performance improves. As shown by Table 3, the accuracy
adding \(\text{fracDev}_r\) or petro50\(_r\) and petro90\(_r\) decreases. Obviously the more parameters
considered, the performance is not always better, sometimes even worse. The results
have shown that there is no improvement in the use of more parametric data from SDSS
and 2MASS catalogs. Hence we would not recommend its use because it decreases the
sample size markedly and does not decrease the rms errors in the photometric redshift
prediction.

### Table 3  
The dispersions of photometric redshift prediction using KR and SVMs.

| method | KR | SVMs |
|--------|----|------|
| Input Parameters | \(\sigma_{\text{rms}}\) (optimal bandwidth) | \(\sigma_{\text{rms}}\) |
| \(u, g, r, i, z\) | 0.0208 \((h = 0.025)\) | 0.0291 |
| \(u, g, r, i, z, J, H, Ks\) | 0.0254 \((h = 0.015)\) | 0.0278 |
| \(u - g, g - r, r - i, i - z\) | 0.0193 \((h = 0.020)\) | 0.0273 |
| \(u - g, g - r, r - i, i - z, r\) | 0.0196 \((h = 0.025)\) | 0.0284 |
| \(u - g, g - r, r - i, i - z, z - J, J - H, H - Ks\) | 0.0210 \((h = 0.045)\) | 0.0273 |
| \(u - g, g - r, r - i, i - z, J - H, H - Ks, r\) | 0.0235 \((h = 0.055)\) | 0.0275 |
| \(u - g, g - r, r - i, i - z, \text{fracDev}_r\) | 0.0192 \((h = 0.020)\) | 0.0306 |
| \(u - g, g - r, r - i, i - z, \text{petro50}_r, \text{petro90}_r\) | 0.0218 \((h = 0.040)\) | 0.0330 |

NOTE.—-petro50\(_r\) is Petrosian 50% radius in \(r\) band, petro90\(_r\) is Petrosian 90% radius in \(r\) band, \(\text{fracDev}_r\) is \(\text{fracDev}\) in \(r\) band.

For KR, the best input patterns includes four colors and \(\text{fracDev}_r\) \((u - g, g - r,
\(r - i, i - z, \text{fracDev}_r\)) when the rms error amounts to 0.0192. The better input patterns
are four colors or four colors and \(r\) magnitude when rms error are 0.0193 or 0.0196,
respectively. Then the good input pattern includes five magnitudes when the rms scatter
is 0.0208. The result with only seven colors is better than that with seven colors and
r magnitude but worse than that with five magnitudes. For four colors as inputs, the performance of kernel regression decreases when adding $\text{petro} 50_r$ and $\text{petro} 90_r$, except for $\text{fracDev}_r$. As a result, when applying kernel regression to predicting photometric redshifts, we find the parameters except magnitudes and color indexes, such as $\text{petro} 50_r$ and $\text{petro} 90_r$, are void, however $\text{fracDev}_r$ is important and effective possibly because $\text{fracDev}_r$ is closely related to galaxy type. When implementing KR, the enlargement of bandwidth may cause less loss of estimation. In our experiments, the fraction of loss is less than 1%. Table 3 also indicates that the optimal bandwidth is different for different input patterns.

To clearly show the performances of KR and SVMs, we take the best and worst results for both approaches, and plot the known spectroscopic redshifts against the calculated photometric redshifts from the test data, shown in Figures 1-2. Figure 1 depicts the results for KR, while Figure 2 gives the results for SVMs. In Figures 1 and 2, the left panel shows the best input pattern, and the right panel plots the worst input pattern. It is clear that, for SVMs, the estimation of photometric redshifts is high for low-redshift galaxies. However, the performance of KR is very satisfactory.

**Fig. 1** Spectroscopic redshift versus calculated photometric redshift comparisons using 20,695 test galaxies from the SDSS DR5 and 2MASS databases with kernel regression. Left figure shows that the best input pattern with $\sigma_{\text{rms}}=0.0192$ is $u - g, g - r, r - i, i - z, \text{fracDev}_r$. Right figure indicates that the worst input pattern with $\sigma_{\text{rms}}=0.0254$ is $u, g, r, i, z, J, H, Ks$.

So far there has been much work on approaches to photometric redshift estimation. To compare the performance of various methods, we list the rms scatters of photomet-
Fig. 2  Spectroscopic redshift versus calculated photometric redshift comparisons using 20,695 test galaxies from the SDSS DR5 and 2MASS databases with SVMs. Left figure shows that the best input pattern with $\sigma_{\text{rms}}=0.0273$ is $u-g, g-r, r-i, i-z$. Right figure indicates that the worst input pattern with $\sigma_{\text{rms}}=0.0330$ is $u-g, g-r, r-i, i-z, \text{petro}50_r, \text{petro}90_r$.

Because the accuracy strongly depends on the data used, we only give a coarse comparison. As shown in Table 4, kernel regression is comparable to artificial neural networks (ANNs), better than SVMs (Wadadekar 2005), Kd-tree (Csabai et al. 2003) and polynomial (Connolly et al. 1995), and superior to CWW and Bruzual-Charlot (Csabai et al. 2003). Nevertheless, each method has its strong and weakness. Kernel regression belongs to the instance-based learning family. It is a kind of memory-based method and learns until prediction. Therefore kernel regression consumes much large memory of a computer in despite of high accuracy. If using ANNs, one should be familiar with the network architecture and make a decision about how many input nodes or hidden layers they have. The more complex networks it has, the more accurate result it earns. However, SVMs may use different kernel functions instead of different ANN networks. As long as you choose the appropriate kernel function and parameters, the rms scatter will decrease significantly. Moreover the classical problems such as multi-local minima, curse of dimensionality and overfitting in ANNs, seldom occur in SVMs. Nevertheless, SVMs need prior knowledge to adjust parameters.

Degeneration between parameters makes the regulating process more complicated. Even though linear or non-linear polynomial regression is easy to implement and communicate with astronomers, the systematic deviation is large (Brunner et al. 1997; Wang et al. 1998; Budavári et al. 2005; Hsieh et al. 2005; Connolly et al. 1995). Csabai et al. (2000)
have represented a hybrid method, which is a combination of template-based and empirical training set. The hybrid one can reconstruct the continuum spectra of galaxies directly from a set of multicolor photometric observations and spectroscopic redshifts. Even though the dispersion of photometric redshifts using this combination technique was significantly improved, it is still worse than empirical ones.

Table 4: Photometric redshift accuracies for various approaches

| Method Name               | $\sigma_{\text{rms}}$ | Data set          | Input parameters |
|---------------------------|------------------------|-------------------|-----------------|
| CWW$^1$                   | 0.0666                 | SDSS-EDR          | ugriz           |
| Bruzual-Charlot$^1$       | 0.0552                 | SDSS-EDR          | ugriz           |
| Interpolated$^1$          | 0.0451                 | SDSS-EDR          | ugriz           |
| Polynomial$^1$            | 0.0318                 | SDSS-EDR          | ugriz           |
| Kd-tree$^1$               | 0.0254                 | SDSS-EDR          | ugriz           |
| ClassX$^2$                | 0.0340                 | SDSS-DR2          | ugriz           |
| SVMs$^3$                  | 0.0270                 | SDSS-DR2          | ugriz           |
| ANNs$^4$                  | 0.0229                 | SDSS-DR1          | ugriz           |
| Polynomial$^5$            | 0.0250                 | SDSS-DR1,GALEX    | ugriz + nuv     |
| Kernel Regression         | 0.0193                 | SDSS-DR5,2MASS    | color$^*$       |
| SVMs                      | 0.0273                 | SDSS-DR5,2MASS    | color$^*$       |

NOTE.—- SDSS-EDR = Early Data Release (Stoughton et al. 2002),
SDSS-DR1 = Data Release 1 (Abazajian et al. 2003),
SDSS-DR2 = Data Release 2 (Abazajian et al. 2004),
SDSS-DR5 = Data Release 5 (Adelman-McCarthy et al. 2007).
color$^*$ is the color indexes, i.e. $u - g$, $g - r$, $r - i$, $i - z$.
(1) Csabai et al. 2003; (2) Suchkov, Hanisch, Margonet 2005;
(3) Wadadekar 2005; (4) Collister, Lahav 2004; (5) Budavári et al. 2005.

5 CONCLUSIONS

We utilize two novel methods, which are Support Vector Machines (SVMs) and Kernel Regression (KR), to estimate photometric redshifts using the cross-matched data from SDSS DR5 and 2MASS. We compare the performances of estimating photometric redshifts with SVMs and KR for different input patterns. Our experiments show that only when the appropriate parameters are chosen, the accuracy of SVMs or KR can improve. Adding additional bandpasses from the infrared (2MASS) contribute little information due to the small size of dataset. In addition, there is no improvement in the use of the parameters ($\text{petro50}_r, \text{petro90}_r, \text{fracDev}_r$) related to angular size and morphology.
The accuracy of photometric redshift produced by SVMs is slightly less than that of ANNs, as good as linear or quadratic regression, and clearly much better than template fitting one. In appropriate situations, SVMs will be a highly competitive tool for determining photometric redshifts in terms of speed and applications. However, it does depend on the existence of a large and representative training sample. As a kind of empirical photometric redshift estimations, SVMs are impossible in extrapolating to the region that is not well sampled by training set. Moreover a potential solution to the problem of increasing the photometric redshift accuracy is to choose the more appropriate kernel function, and to consider the feature selection/extraction methods in the process of parameter selection.

The dispersion of photometric redshift estimation by kernel regression is fairly favorable. Compared to other training-set methods, kernel regression does not need any effort on training. In addition, kernel regression ameliorates a major problem of empirical training-set methods. Even though a few high-redshift galaxies exists in the sample, kernel regression can appropriately adjust bandwidth to obtain much more accurate redshifts. Therefore, kernel regression can extrapolate to regions where the input parameters are not well represented by the training data. With large and deep photometric surveys carried out, it seems that kernel regression will show its superiority. In the future work we will explore adaptive bandwidth or other kinds of distance metric for kernel regression on the regression problems.

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